Drivers and Synergies in the Adoption of Sustainable Agricultural Intensification Practices: A Dynamic Perspective

Ali M. Oumer[1, 2] and Michael Burton[1]

[1]University of Western Australia; Agricultural and Resource Economics; UWA School of Agriculture and Environment, 35 Stirling Hwy, Crawley, WA 6009, Perth, Australia. Email: ali.oumer@research.uwa.edu.au, michael.burton@uwa.edu.au

[2]Ethiopian Institute of Agricultural Research; P.O. Box: 2003, Addis Ababa, Ethiopia

Selected Paper prepared for presentation at the 2018 Agricultural & Applied Economics Association Annual Meeting, Washington, D.C., August 5-7, 2018

Drivers and Synergies in the Adoption of Sustainable Agricultural Intensification Practices: A Dynamic Perspective

Abstract

This paper presents new results on the determinants of adoption of various sustainable agricultural intensification practices (SAIPs) which consist of input-intensive and natural resource management (NRM) activities, using panel data from Ethiopia. It uses a novel statistical approach: a dynamic multivariate probit model which allows for both intertemporal and inter-activity correlation between unobserved factors that may drive adoption. We complement the analysis using an ordered probit model to estimate the degree of adoption. Results reveal complex complementarity and substitution effects, as well as new insights into deterministic factors that influence dynamic adoption. We reveal four significant results of policy relevance. First, the probability of adoption of each practice significantly increases if the household had adopted each practice in a previous period. Second, significant complementarities and trade-offs exist between SAIPs over time. In particular, we reveal positive synergies between input-intensive and NRM practices, underscoring the importance of promoting them as packages. Third, the covariates that drive adoption significantly differ between practices, time and appear to reflect synergistic effects implicit in the practices. Fourth, the likelihood of adoption of more than two SAIPs increases with the variability of historical rainfall, farm size, labour availability, credit, saving, social capital and family education. In particular, the likelihood of adoption increases in less fertile soils and steeper fields, indicating that farmers use combinations of these practices as an adaptive response to soil fertility depletion. By contrast, the likelihood of adoption of more than two SAIPs decreases with the variability of lagged (previous year) rainfall, the variability of temperature, off-farm income, livestock size and the age of the head. These findings can contribute to public and private sector policy design to uplift smallholder agricultural productivity amidst increasing land degradation and climate variability.

Keywords: Technology adoption; Maize; Sustainable agriculture; Synergies; Dynamic multivariate probit; Smallholder farmers; Africa

1. Introduction

Sustainable agricultural intensification is seen as a feasible strategy to enhance smallholder farm productivity with a minimal environmental footprint in Africa. Thus, sustainable agricultural intensification practices (SAIPs) have been widely promoted to raise crop yields and hence, food security while also enhancing environmental resources. The premise is that these twin goals can be achieved by fostering synergistic relationships between the practices, conserving nutrients and increasing the economic efficiency of smallholder farmers (The Montpellier Panel, 2013, World Bank, 2008, Lee, 2005, Lee David et al., 2006, Gollin et al., 2005). While there is a consensus that SAIPs are essential for achieving these goals, there is no consensus about which types of SAIPs are best suited to smallholder farmers in Africa (Wainaina et al., 2016). Broadly, there are two types of SAIPs: input-intensive and natural resource management (NRM) practices. The input-intensive practices include external inputs (e.g. improved seed, chemical fertilizer). The NRM practices include low-external-input agronomic strategies (e.g. reduced tillage, organic manure). In public discussions, these two types of SAIPs are often perceived as incompatible (Wainaina et al., 2016, Koppmair et al., 2017, Hellerstein et al., 2017). Some argue that input-intensive practices with a substantial role of private sectors are most appropriate (Stevenson et al., 2013, Pingali, 2007, Borlaug, 2007), others stress the significant role of NRM practices in light of increasing soil degradation and climate variability (Altieri and Toledo, 2011, Altieri, 2002, De Schutter and Vanloqueren, 2011). Regardless of these different arguments, adoption rates, especially of the NRM practices, remain low despite substantial promotion efforts in the region.

Most previous adoption studies (Wollni et al., 2010, Melinda and John, 2014, Lambrecht et al., 2014, Kathage et al., 2016, Kassie et al., 2010, Becerril and Abdulai, 2010, Gebremedhin and Swinton, 2003) have analysed the drivers of adoption of individual SAIPs using different data and methods, in which comparisons were not easily possible. Moreover, these studies ignore the fact that SAIPs are interdependent (Dorfman, 1996) and can be driven by complex factors that may relate to trade-offs and synergistic effects implicit in the practices. A few recent studies have addressed these shortcomings by modelling multiple SAIPs and a set of covariates simultaneously in a static framework. These studies find that input-intensive and NRM practices are not incompatible as often presumed (Wainaina et al., 2016, Koppmair et al., 2017, Kassie et al., 2015). Instead, positive synergies and trade-offs exist between the two types of practices and the covariates that drive adoption could reflect the synergies that are implicit between the practices. Furthermore, smallholder farmers can make complex sequential adoption decisions. That is, adoption of one technology may drive the adoption of another technology or same technology over time. Therefore, interactivity and intertemporal dynamics could have a positive or a negatives spill-over effect on the adoption behaviour of farmers. In particular, the intertemporal dynamics of SAIPs adoption is critical but has rarely been investigated. Lack of intertemporal dynamics is a core limitation of technology adoption empirical literature (Feder et al., 1985, Doss, 2006). Smallholder farmers' technology adoption decisions and their determinants are inherently dynamic. The likelihood of adoption of SAIPs can depend on whether or not farmers had tried those practices before and evaluated for accrued benefits against costs.

This study addresses these shortcomings by investigating the drivers of adoption and synergies among SAIPs in a dynamic framework. We use nationally representative, balanced panel data of 2031 farm households from maize growing areas of Ethiopia. We consider eight SAIPs which consist of both input-intensive and NRM practices in 2009/2010 and 2012/2013. These SAIPs are improved seed, inorganic fertilizer, crops residue retention, animal manure, soil and water conservation (SWC)[1] measures, legume rotation, legume intercropping, and reduced tillage. We estimate a dynamic multivariate probit (MVP) adoption model that accounts for the fact that farmers make adoption decisions simultaneously, and that there will be interactions between adoptions over time. The dynamic MVP simultaneously models the relationships between multiple SAIPs and a set of covariates by allowing individual-specific unobserved effects to correlate both between the SAIPs and over time. In our context 'adoption' is not an irreversible process, and it is possible for the practices to be adopted, and then subsequently abandoned. The dynamic MVP model offers new insights not only about the simultaneous nature of multiple technologies adoption decisions but also the spill-over effect of time in conditioning sequential adoption. The approach is novel: we are not aware of any research that addressed dynamic interdependencies between SAIPs. Furthermore, we include historical climate and weather variabilities, prices, institutional and policy factors as covariates in the dynamic adoption model. We complement an analysis of the determinants of the extent of adoption of SAIPs (defined as the number of SAIPS adopted) using an ordered probit model.

[1] These include structural techniques such as terraces, soil bunds, stone bunds, grass stripes and box ridges.

We reveal four major results of policy relevance. First, there is a consistency in the impacts of unobservable effects on the probability of adoption of each practice across time: if they were more likely to adopt in the earlier year, then this carries through to the second year. The result underscores the positive spill-over effects of time in conditioning the adoption behaviour of farmers. Although this result may appear to be obvious, given the items under consideration, there is no requirement that once adopted the activity has to be maintained. This result is new in the strands of SAIPs literature. Second, significant complementarities and trade-offs exist among SAIPs. In particular, we reveal important synergies between the input-intensive and NRM practices. Thus, we build on emerging empirical evidence (Wainaina et al., 2016, Koppmair et al., 2017, Kassie et al., 2015) by incorporating our dynamic perspective to challenge the widely-held misperception that these two types of practices are incompatible. Indeed, smallholder farmers adopt input-intensive and NRM practices as complements or as substitutes depending upon their needs and prior experience. Third, we observe that covariates that drive adoption significantly differ between practices, and time, and appear to reflect synergistic patterns implicit in the practices. Fourth, the likelihood of adoption of more than two SAIPs increases with the variability of historical rainfall, farm size, labour availability, access to credit, saving, social capital and family education. In particular, the likelihood of adoption of more than two SAIPs increases in less fertile soils and steeper fields, indicating farmers use combinations of these practices as an adaptive response to reverse soil fertility degradation. By contrast, the likelihood of adoption of more than two SAIPs decreases with the variability of lagged (previous year) rainfall, the variability of temperature, livestock size, the age of the head, and off-farm income.

These results can contribute to the debate within the development economics community on designing effective programs because efforts to promote adoption of one practice may appear to discourage the adoption of another practice if the interdependency between the practices is overlooked. The findings are imperative to design policy across sub-Saharan Africa given its economic growth is intertwined with smallholder agricultural productivity amidst increasing land degradation and climate variability.

2. The theoretical framework of the adoption decision

Households choose a technology or a package of technologies which maximize their expected utility (Von Neumann and Morgenstern, 1947) conditional upon the adoption decision. The farmers value their profits or benefits against costs of adoption of a particular technology. Here, the underlying behavioural assumption is risk aversion. Most technology adoption studies apply the expected utility theory assuming a large proportion of smallholder farmers in developing countries are risk-averse (Wollni et al., 2010, Wainaina et al., 2016, Kassie et al., 2013, Feder et al., 1985, Dorfman, 1996, Arslan et al., 2014). However, there are other competitors to the expected utility theory, such as the prospect theory (Kahneman and Tversky, 1979) based on the assumption of loss aversion. That means smallholder farmers might value losses much more than gains depending on their production circumstances.

We assume that smallholder farmers maximize their expected benefit from adoption as compared from non-adoption of SAIPs. The expected benefits could include labour or input saving as well as increases in output because of improved soil fertility or reduced soil erosion (Wollni et al., 2010, Knowler and Bradshaw, 2007). There can be environmental (ecosystem) benefits beyond farm-level such as reduced downstream sedimentation, reduced flooding and better river flow or wetland resources and carbon sequestration, which can enhance food security and biodiversity to the community (World Bank, 2008, Wollni et al., 2010, Knowler and Bradshaw, 2007). However, the costs of adoption are borne at the farm-level by farmers even though the benefits are also gained by the society as a whole (World Bank, 2008, FAO, 2007). Since smallholder farmers are not getting the full benefits of adoption, they are less likely to adopt NRM practices, and adoption rates often remain below the expected levels (Shiferaw and Holden, 2000, World Bank, 2008).

Nevertheless, smallholder farmers implement both capital-incentive and NRM practices. The input-intensive techniques include improved seed, chemical fertilizer, pesticide and irrigation. Ethiopian farmers rarely use pesticide and irrigation for maize production, similar to Kenyan farmers (Wainaina et al., 2016). Thus, we focus on improved maize seed and chemical fertilizer in our adoption analysis. Here, improved maize seed includes fresh hybrid seeds and open-pollinated varieties recycled at most for three production seasons. The NRM practices involve different low–external input strategies which are mostly implemented to curb soil erosion and hence, reverse land degradation. These NRM practices include improved agronomic strategies such as conservation agriculture (crop residues, legumes rotation, legumes intercropping and reduced tillage), SWC measures, and organic manure. A detailed description of these practices and their agro-environmental benefits can be found in the literature (Wollni et al., 2010, Wainaina et al., 2016, Teklewold et al., 2013, Stevenson et al., 2014, Lee, 2005, Kassie et al., 2013) and references therein.

3. The dynamic multivariate probit model

Adoption decisions of multiple technologies are interdependent on the same farm. Smallholder farmers deal with multiple agricultural production constraints, which necessitates the adoption of both input-intensive and NRM practices. A few recent studies have employed a static multivariate probit model to reveal such interrelationships (Wainaina et al., 2016, Koppmair et al., 2017, Kassie et al., 2015). However, technology adoption decisions and their driving factors are inherently dynamic. Therefore, we use a dynamic multivariate probit (MVP) model that accounts for correlation in unobserved and unmeasured factors (error terms) across practices, a set of covariates and time.

The dynamic MVP model consists of eight binary choice equations in each period. The eight binary choices represent the SAIPs, namely improved seed, chemical fertilizer, crop residues, reduced tillage, SWC measures, legumes rotation, legume intercropping and organic manure. The general model can be written as:

$$y^*_{itm} = x'_{itm}\beta_m + \varepsilon_{itm}, \tag{1}$$

$$y_{itm} = \begin{pmatrix} 1 \text{ if } y^*_{itm} > 0 \\ 0 \text{ otherwise} \end{pmatrix}, \tag{2}$$

where: y^*_{itm} is a latent variable that captures the expected benefit from adopting a SAIP m in the period t. In a dynamic perspective, a farm household could use a SAIP in a previous period, have trailed it and seen accrued benefits which may have positive or negative effects on the adoption of the practice in the next period. The dynamic model consists of eight SAIPs in each period (t =1, 2) giving a total of 16 binary choices. The latent variable y^*_{itm} is assumed to be a linear combination of various covariates x'_{itm} and the unobserved error term, ε_{it}. Because y^*_{itm} is implicit (latent) which means not observable, the estimation is based on the observed binary choices y_{itm}, which indicates whether or not a farm household i implemented a particular SAIP m in the reference period t. The error terms ε_{itm} jointly follow a multivariate normal distribution each with mean zero and a variance normalized to one. The model generates a variance-covariance matrix that describes correlation of unobserved factors across the two periods, and the SAIPs. A positive correlation indicates complementary technologies or positive spill-over effect of time, whereas a negative correlation indicates substitution or an adverse spill-over effect of time. The maximum-likelihood function of the multivariate normal distribution requires multidimensional integration, which can be correctly estimated by simulation methods (Cappellari and Jenkins, 2003).

We complement our analysis by estimating determinants of the number of practices adopted per farm (degree of adoption) using an ordered probit model. Because of partial adoption (Wollni et al., 2010, Teklewold et al., 2013), it is difficult to quantify the area under the SAIPs packages and hence, we use the number of SAIPs as a dependent variable. Here, the ordered probit model is justified because SAIPs are interdependent and the probability of adoption of each of the practices differ (Wollni et al., 2010). The underlying assumption for the ordered probit model is again a random utility framework. The ordinal dependent variable is defined as $y_{it} = 0,1,2...6$. The ordinal dependent variable indicates that farmers may adopt zero $(y_{it} = 0)$, one $(y_{it} = 1)$, two $(y_{it} = 2)$, three $(y_{it} = 3)$, four $(y_{it} = 4)$, five $(y_{it} = 5)$ or adopt more than five $(y_{it} = 6)$ different SAIPs. The latent variable (Greene, 2016) can be written as:

$$y_{it}* = \beta' x_{it} + \varepsilon_{it}, \qquad (3)$$

where: $y_{it}*$ denotes the latent choice variable, x_{it} for covariates and a vector of parameters to be estimated, β. The unobserved random error term ε_{it} with mean zero and variance of one. While we do not observe $y_{it}*$ but we know:

$$
\begin{aligned}
y_{it} &= 0 \text{ if } \mathrm{y}_{it} \leq \mu_1, \\
&= 1 \text{ if } \mu_1 < y_{it} \leq \mu_2, \\
&= 2\ 1 \text{ if } \mu_2 < y_{it} \leq \mu_3, \qquad (4) \\
&\ldots \\
&= j \text{ if } y_{it} > \mu_{j-1}.
\end{aligned}
$$

Where: $\mu_1 < \mu_2 .. < \mu_{J-1}$ are unknown threshold parameters to be estimated with β. The ordinal dependent variable for the number of SAIPs $y_{it} = 0,1,...j$. The probabilities of adoption of SAIPs is $\text{Prob}[y_{it} = j]$ which is equivalent to the probability of $y_{it}*$ in the j-th range. We also calculate marginal effects using the delta method (dy/dx) at the means following the recent literature (Wollni et al., 2010, Greene, 2016).

4. Research context, data and adoption covariates

4.1 Research context

Ethiopia's economic performance is heavily dependent on rainfed agriculture. The agriculture sector contributes about 40% of the national GDP, 90% of exports and 85% of employment. Smallholder farm households cultivating land areas below a hectare for subsistence purposes account for about 95% of the national agricultural output. Climate variability poses serious risks to the stability of crop yields and food security (Di Falco and Veronesi, 2014, Di Falco, 2014). Soils also tend to be degraded. Cereals production account for 73% of the cropped land. Among cereals, maize is the key national staple crop grown by millions of smallholder farm households. These farm households account for more than 95% of the total maize area and production in the country. Maize production is predominantly rainfed, and only 1% of the total maize area is irrigated (Abate et al., 2015). The majority of farm households are resource-poor and often forced to pursue continuous maize mono-cropping and undertake extractive farming practices such as the removal of crop residues and animal manure. Such extractive farming practices coupled with other factors have resulted in varying and stagnant maize yields associated with depletion of soil resources. As such, sustainable intensification of crop production systems has become an important economic and policy issue in the country. Smallholder farm households use a range of SAIPs to mitigate the negative effects of soil fertility depletion and climate variability. The general farming context is also similar across many countries in sub-Saharan Africa.

4.2 Data

This study is based on farm household data collected from maize growing areas of Ethiopia. The data were collected in 2010 and 2013 by the Ethiopian Institute of Agricultural Research (EIAR) in collaboration with the International Maize and Wheat Improvement Centre (CIMMYT). The data are nationally representative and collected to ensure complete geographic and agro-ecological coverage of maize farming system (Figure 1).

A multistage sampling procedure was used to select study villages from each district and farm households from each village. First, about 39 districts were selected based on maize production potential from five regional states namely, Oromia, Amhara, Tigray, Ben-Shangul-Gumuz, and Southern Nations and Nationalities Peoples Region (SNNPR). A proportionate random sampling procedure was used to select 3 to 6 villages in each district and 10 to 24 farm households in each village. The surveys used to collect these data were comprehensive and included detailed information about production activities and farm management practices. We use a balanced panel of 2031 farm households in 2009/2010 and 2012/2013 for our dynamic adoption analysis.

< Insert Figure 1 around here >

The data on production inputs and output, SAIPs and farm-related covariates were collected at the plot level. Typically, farm households vary the size and type of plot they allocate to maize production over different periods. Thus, we constructed panel data at the farm (household) level. Such aggregation strategies are common in empirical research (Ndlovu et al., 2014, Bezabih and Sarr, 2012, Udry, 1996, Alem et al., 2010). The household level data are matched with village level climate data using global positioning system (GPS) coordinates that were obtained during the farm household surveys.

4.3 Technology adoption covariates

A range of factors (covariates) can drive the adoption of SAIPs. These include but are not limited to climatic factors, input-output prices, farm characteristics, socioeconomic and institutional factors as well as personal factors. We include a number of such covariates in our dynamic adoption model following the existing theoretical and empirical literature (Doss, 2006, Wainaina et al., 2016, Marenya and Barrett, 2007, Lee, 2005, Knowler and Bradshaw, 2007, Kassie et al., 2010, Gollin et al., 2005, Feder et al., 1985). The significance and direction of influence of these covariates can depend on the nature of the technology, as well as interdependencies between practices and temporal dynamics. A few studies provide an estimate of the prior direction of influence of these covariates on SAIPs (Wainaina et al., 2016, Knowler and Bradshaw, 2007). We briefly describe these covariates in the context of our study.

Climate and weather patterns can influence adoption behaviour. Both past and current weather patterns can shape smallholder farmers' livelihood portfolios as well as, the management practices they implement (Sesmero et al., 2018, Asfaw et al., 2016, Arslan et al., 2015). Thus, we include historical annual rainfall and its variability in the analysis. We also included the variability of lagged year (previous year) rainfall because of its expected negative impact on the adoption of input-intensive practices (Teklewold et al., 2017, Bezabih and Sarr, 2012, Alem et al., 2010). Likewise, we control for historical maximum temperature and its coefficient of variation.

Prices of inputs and output could also influence the adoption of technologies. We include the prices of chemical fertilizer, labour and seed, which are normalized by the maize grain price. Most adoption studies do not include prices in their analysis due to either lack of data or variation within the sample.

Farm characteristics can drive the adoption of SAIPs. We include soil fertility status and slope of the farm as crucial covariates. We also include altitude to capture agro-ecological differences of the farming households. The proximity of cultivated land to homestead also can influence the adoption of technologies.

Socioeconomic and institutional factors can affect technology adoption. We include age, education and gender of the farming household head. We also control for the education level of other household members to capture the intra-household dynamics in the adoption decision (Asfaw and Admassie, 2004; Doss, 2006). Farm size (maize area), total livestock units (TLU), adult equivalent labour are included as indicators of resource availability. We also include policy-related variables such as credit, cash savings and off-farm income. We also included asset value as a measure of household's wealth. Furthermore, we included indicators of institutional/social capital: access to supportive institutions, relatives, a trust of grain traders, information, tenure status, and distance to the nearest input market. As also highlighted by Wainaina et al. (2016), some of these covariates may be endogenous, which means that the parameter estimates in the results section should not be interpreted as causal. Here, our main focus is on the direction and the significance of covariates with SAIPs adoption. Table 1 presents descriptive statistics for SAIPs and the covariates used for the empirical analysis.

< Insert Table 1 around here >

5. Results and Discussion

5.1 Trade-offs and synergies between practices

Before presenting the drivers of SAIPs adoption, we discuss the results of the error term correlation matrix which provides the interrelationships between the practices. Based on the likelihood ratio test, we reject the null hypothesis of zero correlation between the error terms at 1% significance level. This result suggests that the dynamic MVP model is preferred over the single-equation probit models. In this section, we focus on trade-offs and synergies between the different practices as well as the spill-over effects of time in conditioning the adoption of SAIPs. A positive correlation indicates complementary technologies or positive spill-over impact of time, whereas a negative correlation indicates substitution or an adverse spill-over effect of time. In some cases, the negative correlation also could reflect compatibility of the practices across a range of production domains (Wainaina et al., 2016).

Table 2 presents the results of interactivity and intertemporal adoption of the practices based on the correlation matrix from the dynamic MVP model. The estimation results reveal evidence of interdependencies among the practices. The results can be read in three panels. The top left-hand panel gives the correlation between practices, when $t=1$. The lower right-hand panel gives the correlation between practices, when $t=2$. The lower left panel gives the correlation between practices, *across time.* Hence the leading diagonal of the lower left panel shows the correlation for each practice with itself, across the two time periods. These results demonstrate a highly statistically significant correlation among the practices in both periods. These results suggest that the adoption of one practice could drive the adoption of another practice. These results are consistent with recent studies that reported interdependencies among SAIPs (Wainaina et al., 2016, Koppmair et al., 2017, Kassie et al., 2015, Kassie et al., 2013). These studies, however, were based on a static framework and had not addressed the temporal dynamics of the adoption decision.

Our results demonstrate that the probability of adoption of each practice is significantly correlated across time. These are shown by the positive and highly statistically significant correlation of each practice over time as shown in the lower-left hand panel of Table 2 (e.g. CF_{t_2} vs. CF_{t_1}, CR_{t_2} vs. CR_{t_1}, etc.). The results underscore the positive spill-over effects of time in conditioning the adoption behaviour of farmers. This result is new in the strands of SAIPs literature.

<Insert Table 2 around here>

The results also reveal complementarities and trade-offs among SAIPs. In particular, the results reveal important synergies between modern inputs and NRM practices. In 2009/2010, inorganic fertilizer has a significant negative association with crop residues, manure and minimum tillage, but a significant positive association with improved seed and legume intercropping (top left panel). Also, the use of improved seed has a significant negative association with minimum tillage and legume intercropping but a significant positive association with legume rotation. We find similar results in 2012/2013 (bottom right panel). The interactivity correlations over time also reveal consistent results. Our findings are consistent with recent studies that provide evidence on the beneficial synergies using those practices in a static framework (Wainaina et al., 2016, Koppmair et al., 2017). Thus, we build on this early evidence by incorporating our dynamic perspective to challenge the widely-held misperception that these two types of practices are incompatible. Indeed, smallholder farmers adopt input-intensive and NRM practices as complements or as substitutes depending upon their needs and prior experience.

Interestingly, we revealed many positive correlations between the two types of practices for Ethiopian farmers. This result implies that beneficial synergies or positive complementarities can be exploited by use of input-intensive practices (improved seed or chemical fertilizer) with the conservation agriculture practices (The Montpellier Panel, 2013, World Bank, 2008, Lee, 2005, Gollin et al., 2005, Kassie et al., 2015). This result is in contrast with Wainaina et al. (2016) who find a few positive correlations between the input-intensive and NRM practices for Kenyan farmers. These contrasts underscore the importance of niche-tailored development pathways to achieving sustainable agricultural intensification in Africa (Stevenson et al., 2014, Lee David et al., 2006, Knowler and Bradshaw, 2007). It is also imperative to assess whether or not the observed interdependencies in the practices influence the drivers of adoption. We discuss these issues in the next sections.

5.2 Drivers of dynamic technology adoption

In the previous section, we analysed interactivity and intertemporal correlation and revealed beneficial synergies and trade-offs between input-intensive and NRM practices. In this section, we focus on the driving factors of adoption with particular attention to possible differences in the covariates between input-intensive and NRM practices. As pointed out by Wainaina et al. (2016) systematic differences in the drivers (covariates) could indicate that each type of practice is used under different conditions, whereas similarities in the covariates could suggest that different types of practices may be possible under similar settings. We also investigate whether or not the drivers (covariates) reflect certain patterns of complementarity and trade-offs implicit in the practices across both periods.

Table 3 presents the coefficient estimates from the dynamic MVP model. The coefficient estimates indicate the direction and significance of the association between the SAIPs and covariates for adoption in a dynamic perspective. We find evidence that factors that drive adoption differ between practices. While certain factors mainly drive the adoption of NRM practices, others influence the adoption of input-intensive practices, and such patterns appear to reflect the complementarity and trade-offs implicit in those practices. We also observe that some of the drivers of adoption differ across the two periods[2]. Below, we discuss these results.

Climate factors are found to have a significant association with SAIPs adoption. We find that historical abundance of rainfall has a significant association with the adoption of SAIPs, but with different signs. For example, it increases the likelihood of adoption of reduced tillage, residue retention, inorganic fertilizer and legume intercropping but decreases the probability of adoption of improved seed and legume rotation; all else equal. The variability of historical rainfall also has similar effects. However, the variability of lagged (past year) rainfall increases the likelihood of adoption of SWC, organic manure, reduced

[2] We tested the null hypothesis that the coefficients of covariates for each of the practices across the two periods are equal and we reject the null by the likelihood ratio test at 1% level of significance level.

tillage and inorganic fertilizer but decreases the probability of adoption of improved seed, residue retention and legumes intercropping. The variability of lagged rainfall has a significant association with many of SAIPs in both periods. In particular, it had a significant positive association with the adoption of improved seed in the first period but had a reverse effect in the second period. The result underscores the relevance of understanding the temporal dynamics of technology adoption (Doss, 2006, Feder et al., 1985). Not surprisingly, higher temperature increases the likelihood of adoption of residue retention, organic manure, improved seeds and legume intercropping but decreases the probability of adopting reduced tillage. The variability of historical temperature is also more likely to increase the likelihood of adoption of crop residues, reduced tillage and legume intercropping but tend to decrease the probability of adopting modern inputs (improved seed and inorganic fertilizer). The results underscore the importance of climate factors in explaining heterogeneity in the dynamic adoption of multiple practices which can have subsequent weather-induced welfare impacts (Teklewold et al., 2017, Sesmero et al., 2018, Arslan et al., 2015). However, most previous adoption studies do not control climate factors due to lack of georeferenced climatology data.

<Insert Table 3 around here>

Input prices (normalised by maize grain price) also explain dynamic adoption decision. The price of fertilizer increased the likelihood of adoption of chemical fertilizer and improved seed (complementary inputs) in the first period but decreased their likelihood of adoption in the second period, *ceteris paribus*. It also has a positive association with the adoption of crop residues and manure but a negative association with the adoption of SWC measures. Higher seed price is more associated with increased adoption of complementary practices such as improved seed and chemical fertilizer and, these results are consistent across the two periods. By contrast, higher seed price has a negative association with the adoption of NRM practices except for SWC measures in the second period. The negative association between legume intercropping and higher seed price could be due to its complementarity with the input-intensive practices such as improved seed or chemical fertilizer. Likewise, labour price appears to be positively associated with the NRM practices except legume intercropping and negatively associated with the input-intensive practices. It appears that the nature of SAIPs interrelationships, their complementary and trade-off patterns and temporal dynamics play roles in conditioning the adoption process. The results underline the relevance of understanding the temporal dynamics and interrelationships among practices when investigating the drivers of adoption.

Among the socioeconomic characteristics, family labour availability has a positive association with many of SAIPs but a negative association with reduced tillage. The results reinforce the critical role of labour in driving the adoption of SAIPs (Doss, 2006, Lee, 2005, Lee David et al., 2006, Gollin et al., 2005). Conversely, the adoption of minimum tillage appears to be a response to lack of labour. The results also reveal that education level of household members and education level of the household head appear to have differential effects on the likelihood of SAIPs adoption. A higher level of education of family members has a significant positive association with the likelihood of adoption of modern inputs such as (improved seeds or chemical fertilizer) and their NRM complement, legume rotation. However, the education level of the household head has the reverse effect. Contrarily, the education level of the household head is positively associated with the adoption of reduced (minimum) tillage. These results underscore the fact that group decisions are made contrary to what is often presumed because of the skewed emphases given to the household head. The results are consistent with (Asfaw and Admassie, 2004) who revealed education of family members to be more critical than the education level of the household head for fertilizer adoption in Ethiopia. Similarly, Wollni et al. (2010) found education level of family members to have a positive association with the adoption of SWC measures in the Honduran hillsides. Thus, understanding intra-household dynamics sheds light regarding the adoption of SAIPs. Age of the household head is also negatively associated with adoption of SAIPs except for reduced tillage. Given the rapid youth migration to urban areas for better wages, enhancing the sustainability of land degradation in Ethiopia and elsewhere could be undermined especially for the labour-intensive NRM practices. Our results also show that male household heads are more likely to implement inorganic fertilizer, SWC measures and legume intercropping than female-headed households. On the other hand, female-headed households are more likely to apply manure possibly because of the proximity of their farms to homestead.

Households' resource endowment also matter in driving SAIPs adoption. Strikingly, farm size is found to drive the adoption of all the SAIPs. By contrast, off-farm income is found to have the reverse effect. The result suggests that off-farm work might take away farm labour that could have been used to implement SAIPs. Alternatively, cash from the off-farm income may not have been transferred to invest in the use of SAIPs. These results point to the need to be cautious when promoting linkages between farm and non-farm activities in developing countries where markets are imperfect (Haggblade et al., 1989, Chavas et al., 2005). Lack of oxen or livestock is also negatively associated with the adoption of modern inputs (chemical fertilizer and improved seed), and their NRM complement, organic manure. Farmers also appear to implement reduced tillage and legume intercropping when they face oxen constraints. Higher assets value (wealth) positively influences the adoption of both modern and NRM practices.

Institutional factors are also key drivers of SAIPs adoption. A having higher institutional capital as proxied by the number of supportive institutions has a significant positive association with the adoption of SWC measures, improved seed and chemical fertilizer. This result could relate to the differential roles of private and public sector extension services in expanding these practices. However, the institutional capital is negatively associated with the adoption of residue retention and reduced tillage, which are the two pillars of conservation agriculture. This result could be due to lack of proper farm power to implement conservation agriculture practices (Temesgen et al., 2009, Hobbs et al., 2008, Baudron et al., 2015). Ethiopian farmers use inefficient traditional oxen-drawn power for ploughing their farm. Farmers are also more likely to implement SWC measures, crop residues and legume rotation on their farms relative to rented farms. However, they tend to use a relatively more improved seed on rented farms. Access to credit is positively associated with the probability of adoption of inorganic fertilizer, and improved seed, which is expected given credit is primarily geared toward the promotion of these modern inputs. Savings of cash also appear to drive the adoption SAIPs. Having higher social capital as indicated by access to trusted grain traders and having many relatives in the village, access to mobile phone and proximity of input market also play significant roles in the adoption of SAIPs albeit with different signs for the various practices.

Farm characteristics also significantly influence the adoption behaviour of farmers. Consistent with the previous literature (Wollni et al., 2010, Gebremedhin and Swinton, 2003, Wainaina et al., 2016, Marenya and Barrett, 2007), the probability of adoption of SWC, reduced tillage and crop residue increases in stepper farms where they are needed to curve soil erosion. The input-intensive practices (chemical fertilizer and improved seed), as well as their NRM substitutes such as legume rotation and manure, are less likely to be implemented in stepper farms. Farmers are more likely to adopt input-intensive practices (improved seed and chemical fertilizer) in less fertile soils possibly to combat soil fertility depletion. However, they are more likely to apply manure around homestead areas because it is labour-incentive to transport to distant farms. On the other hand, farmers are more likely to use chemical fertilizer, crop residues and legume rotation on distant farms. Finally, chemical fertilizer, improved seeds and organic manure are more likely applied in the high land areas, whereas minimum tillage and legume rotation are more probably constructed in the low land areas. These results could be related to the niche of the agro-ecology of the farming system that is more favourable to certain SAIPs than others. Such niche-targeting of SAIPs were also observed for Kenyan maize farmers (Wainaina et al., 2016). The adoption of legume intercropping is found to be time-dependent; positively associated in the first period but negatively associated in the second period.

5.3 Determinants of the extent of adoption of practices

In the previous section, we discussed the factors that drive the probability of adoption of the practices. In this section, we discuss determinants of the number of practices used on a farm to capture the extent (degree) of adoption. Table 4 shows the results from the random effects ordered probit model[3]. The results show that historical rainfall, variability of lagged rainfall, seed price, family labour, farm size, family education, access to credit, household asset, being male household head, saving of cash, social capital (traders and relatives) and institutional support have significant positive effects on the number of SAIPs adopted. Further, farmers appear to implement a relatively higher number of SAIPs on less fertile soils and steeper fields. By contrast, off-farm income, livestock size, the age of head, altitude, and distance of farm from homestead have a significant negative effect on the number of SAIPs adopted. Farmers are more likely to implement more SAIPs in the second period compared to the first period indicating the positive spill-over effect of time on the extent of technology adoption (see also section 5.1).

[3] The likelihood ratio test suggests that we reject the pooled ordered probit model in favour of the random effects ordered probit model at 1% significance level. However, the two models are numerically similar.

<Insert table 4 around here>

Because the coefficients of ordered probit model are not readily interpretable (Wollni et al., 2010), we report marginal effects that reveal the impact of changes in the covariates on the response probabilities as shown in Table 5. We observe that given the rainfed nature of maize production, the variability of rainfall in the previous year is critical for the extent of adoption of SAIPs. For every additional increase in the coefficient of rainfall variation in the past year, the probability of applying more than two SAIPs decreases by 40% but the variability of historical rainfall has the reverse effect (see also section 5.2). Farmers appear to make short-term and long-term decisions corresponding to current weather and long-term climate patterns as also observed by Sesmero et al. (2018).

<Insert table 5 around here>

With regards to the non-climate factors, the likelihood of adopting more than two SAIPs decreases by 13.2% with a percentage increase in the share of off-farm income. Age of the household head and altitude also have a negative but negligible impact on the adoption of more than two SAIPs. On the other hand, a few variables are found to drive the extent of adoption of multiple SAIPs. The probability of adopting more than two SAIPs increases by 16.3% in the second period compared to the first period. This result underscores the positive spill-over effect of time in the adoption of technology as discussed in section 5. Each additional hectare of farm increases the probability of adoption of more than two SAIPs by 8%. Farmers that save cash are 6% more likely to adopt more than two SAIPs. Similarly, farmers that have access to credit are 3.2% more likely to implement three or more SAIPs. The likelihood of adoption of more than two SAIPs also increases in less fertile soils and in steeper fields suggesting that combinations of these practices are also implemented to reverse the problem of soil degradation. Many other covariates appear to have a positive but negligible impact on the likelihood of adoption of more than two SAIPs.

6. Conclusions and policy implications

We use nationally representative panel data from Ethiopia to analyse the drivers and synergies in the adoption of sustainable agricultural intensification practices (SAIPs). The SAIPs we consider include two main types, namely input-intensive and natural resource management (NRM) practices. The input-intensive practices include improved maize seeds and inorganic fertilizer, and the NRM practices include soil and water conservation (SWC) measures, organic manure, crop residue retention, reduced tillage, legume rotation and legume intercropping. We used a dynamic MVP model that allows not only interactivity correlation but also an intertemporal correlation of the technologies adopted. We also complement our analysis using an ordered probit model to reveal the extent of adoption of the practices while recognizing interdependencies among them.

We reveal four important findings of relevance to policy. First, we find the probability of adoption of each practice significantly increases if the household had adopted each practice in the previous period. The result underscores the positive spill-over effect of time in conditioning the adoption of multiple SAIPs by smallholder farm households. This result is new in the strands of SAIPs literature. These findings point to the need for continuity of programs aimed at promoting SAIPs in smallholder agricultural systems.

Second, we find clear evidence of complementarities and trade-offs among SAIPs. In particular, we reveal many positive synergies between modern inputs and NRM practices for Ethiopian maize farmers over time. Thus, we build on the emerging evidence (e.g. Wainaina et al., 2016, Koppmair et al., 2017, Kassie et al., 2015) by incorporating our dynamic perspective to challenge the widely-held misperception that these two types of practices are incompatible. Indeed, smallholder farmers adopt modern inputs and NRM practices as complements or as substitutes depending upon their needs and prior experience. These results underline the relevance of implementing both input-intensive and NRM practices to bring a steady, sustainable agricultural intensification in predominantly capital-deficient and environmentally-degraded production systems of sub-Saharan Africa.

Third, we find clear evidence that factors that drive adoption differ between practices. For instance, the variability of historical rainfall and temperature increase the likelihood of adoption of certain NRM practices (e.g. crop residues and SWC), whereas the variability of lagged (past year) rainfall variation conditions the use of input-intensive practices such as improved seed and chemical fertilizer. Strikingly, we find farm size to increase the likelihood of adoption of all SAIPs while off-farm income has the reverse effect. This farm and off-farm disconnect in the adoption process calls for policy attention when designing programs to promote SAIPs. We also observe that the factors that drive SAIPs appear to reflect the complementarity and synergistic patterns implicit in those practices.

Fourth, the likelihood of implementing more than two SAIPs (degree of adoption) increases with the variability of historical rainfall, farm size, labour availability, access to credit, saving, social capital and family education. In particular, the likelihood of adoption of two or more SAIPs is likely to increase in less fertile soils and steeper fields, indicating farmers use combinations of these practices to mitigate soil degradation. By contrast, the likelihood of adoption of two or more of SAIPs decreases with the variability of lagged (previous year) rainfall, the variability of historical temperature, livestock size, the age of the household head, off-farm income, altitude and distance of farm from the homestead.

Overall, our findings contribute to the debate within the development economics community on designing effective programs. This is so because efforts to promote adoption of one practice may appear to discourage adoption of another practice due to lack of understanding of the underlying interdependencies among the practices. The results can also offer insights for public and private sectors that support the widespread adoption of these practices by smallholder farmers. The findings can also be imperative for policymakers in African given its economic growth is intertwined with smallholder farm productivity amidst increasing soil degradation and climate variability. As also argued by Wainaina et al. (2016), the underutilization of external inputs in the African smallholder sector calls for a balanced use of a portfolio of SAIPs with both input-intensive and NRM practices to induce a sustainable productivity growth. A piecemeal linear approach of promoting these technologies may not bring intended outcomes: increasing productivity while ensuring environmental sustainability. More research on the tangible impacts of these practices including the combinations that lead to a maximal benefit to smallholder farmers including offsetting production risks would be useful in guiding niche-tailored program design. There could also be a possibility of direct incentive payments (World Bank, 2008, FAO, 2007) to smallholder farmers in developing countries such as Ethiopia for the ecosystem services they could potentially provide for the society. Further research should investigate these issues in depth.

Acknowledgements

We wish to acknowledge the Australian Government (John Allwright Fellowship) through Australian Centre for International Agricultural Research (ACIAR) for funding the research. Ethiopian Institute of Agricultural Research (EIAR) and the International Wheat and Maize

Improvement Centre (CIMMYT) are acknowledged for access to raw data. We would like to acknowledge the National Meteorology Agency (NMA) of Ethiopia for access to climatology data. We would like to thank Menale Kassie for helpful discussions. We would like to thank Chilot Yirga for facilitating data cleaning and management. We thank farmers, supervisors, enumerators and other technical staff and researchers from various partner institutions who contributed to the data collection process. The usual disclaimer applies. All remaining errors are ours.

Table 1: Variable lists and descriptive statistics

Variable name	Variable definition	2009/2010		2012/2013	
		Mean	SD	Mean	SD
Sustainable agricultural intensification practices (SAIPs)					
Chemical fertilizer	=1 if farmer used soil and water conservation (SWC) practices, 0 otherwise	0.66	0.47	0.73	0.45
Crop residues retention	=1 if farmer left any crop residues on farm in previous season, 0 otherwise	0.29	0.46	0.18	0.39
Manure	=1 if farmer used animal manure, 0 otherwise	0.51	0.50	0.48	0.50
Improved seeds	=1 if maize seeds used are improved varieties, 0 otherwise	0.34	0.47	0.66	0.47
Minimum tillage	=1 if farmer's average ploughing frequency was at least two, 0 if above two	0.16	0.36	0.13	0.33
Legume rotation	=1 if farmer rotated maize with legumes, 0 otherwise	0.12	0.32	0.07	0.26
SWC	=1 if farmer applied chemical fertilizers, 0 otherwise	0.23	0.42	0.32	0.47
Legume intercropping	=1 if farmer intercropped maize with legumes, 0 otherwise	0.16	0.36	0.28	0.45
Climate factors					
Rainfall abundance	Long-term average annual amount of rainfall in 100mm (1990-2011)	13.00	3.69	12.98	3.63
Historical rainfall variability	Coefficient of variation of long-term annual rainfall (1990-2011)	0.12	0.02	0.13	0.02
Lagged rainfall variability	Coefficient of variation of monthly rainfall of lagged years (2008 and 2011)	0.88	0.14	0.94	0.17
Temperature variability	Coefficient of variation of monthly maximum temperature (1990-2011)	0.03	0.02	0.03	0.02
Maximum temperature	Average long-term maximum temperature (°C) (1990-2011)	27.11	2.06	27.14	2.04
Prices					
Fertilizer price	Relative fertilizer price, normalized by the grain price of maize output	3.18	1.19	2.93	0.67
Improved seed price	Relative improved seed price, normalized by the grain price of maize output	6.31	2.90	4.43	1.89
Labour price	Relative labour price, normalized by the grain price of maize output	9.33	4.37	4.63	2.33
Household socioeconomic characteristics					
Family labour	Household labour availability converted into adult equivalent	4.92	1.96	5.08	1.91
Family education	Average education level at the household (years of schooling) for age >=7	2.99	2.01	3.06	1.95
Education level of head	Education level of the household head (years of schooling)	3.00	3.31	2.98	3.32
Farm size	Farm size allocated for maize in hectares	0.91	0.82	0.74	0.67
Ox0	=1 if farmer has no oxen, 0 otherwise	0.19	0.39	0.26	0.44
Ox1	=1 if farmer has one ox, 0 otherwise	0.25	0.43	0.26	0.44
TLU	Total livestock holding in tropical livestock units	6.28	5.80	6.00	5.51
Ln asset value	Logarithm of farmer's asset value in Birr	8.86	1.31	9.76	1.31
Off-farm income	Share of off-farm cash in total cash revenue	0.22	0.28	0.25	0.29

Saving	=1 if farmer had savings, 0 otherwise	0.50	0.50	0.46	0.50
Credit	=1 if farmer has access to credit, 0 otherwise	0.16	0.36	0.31	0.46
Gender	=1 if household head is male, 0 if female	0.93	0.26	0.93	0.25
Age	Age of the household head	42.05	12.71	44.63	12.79
Farm characteristics					
Soil fertility	Soil fertility status as perceived by the farmer (1=good, 2=medium, 3=poor)	1.60	0.55	1.53	0.57
Slope of field	Type of slope as perceived by farmer (1=flat, =medium, 3=steep)	1.36	0.49	1.35	0.52
Altitude	Altitude on which the household is located in metres above sea level	17.73	2.67	17.73	2.67
Ln plot distance	Logarithm of average plot walking distance from the residence in minutes	1.67	1.14	1.56	1.21
Institutional/Social capital					
Institutions	Number of institutions farmer is member of in the village	2.64	1.52	2.67	2.03
Ln distance to inputs	Logarithm of distance to input markets	1.45	0.98	1.30	0.90
Traders	Number of grain traders farmer knows and trusts	2.03	4.28	2.08	4.00
Relatives	Number of relatives farmer has in and outside the village	11.61	14.07	17.93	22.94
Information	=1 if farmer has mobile phone, 0 otherwise	0.19	0.39	0.49	0.50
Tenure	Share of owned land area allocated in total maize area	0.82	0.33	0.89	0.26

Notes: SD= Standard deviation.

Table 2: Correlation matrix for the dynamic multivariate probit model

		2009/2010 = t_1								2012/2013 = t_2							
		CF_{t_1}	CR_{t_1}	M_{t_1}	IS_{t_1}	MT_{t_1}	LR_{t_1}	SWC_{t_1}	LI_{t_1}	CF_{t_2}	CR_{t_2}	M_{t_2}	IS_{t_2}	MT_{t_2}	LR_{t_2}	SWC_{t_2}	LI_{t_2}
2009/2010 =t_1	CF_{t_1}	1															
	CR_{t_1}	-0.10**	1														
	M_{t_1}	-0.12***	0.06	1													
	IS_{t_1}	0.45***	-0.19***	-0.13***	1												
	MT_{t_1}	-0.41***	0.07	0.07	-0.33***	1											
	LR_{t_1}	0.22***	0.02	-0.02	0.17***	-0.04	1										
	SWC_{t_1}	0.06	0.03	0.12***	-0.04	0.10**	0.07	1									
	LI_{t_1}	0.04	0.01	0.11**	-0.34***	0.22***	0.07	0.12**	1								
2012/2013 = t_2	CF_{t_2}	0.52***	-0.05	0.01	0.13***	-0.14***	0.08	0.08*	0.19***	1							
	CR_{t_2}	-0.17***	0.13***	-0.02	-0.10**	0.09	0.07	0.09*	-0.03	-0.06	1						
	M_{t_2}	-0.04	-0.08**	0.18***	-0.01	-0.03	-0.16***	0.07*	0.03	-0.09**	-0.09**	1					
	IS_{t_2}	0.34***	-0.12***	0.01	0.22***	-0.22***	0.19***	-0.02	0.07	0.67***	-0.11**	-0.01	1				
	MT_{t_2}	-0.19***	0.04	-0.06	-0.15**	0.47***	0.03	0.07	0.14**	-0.28***	-0.03	-0.09*	-0.33***	1			
	LR_{t_2}	0.16**	-0.03	-0.02	0.13**	0.05	0.21***	0.06	-0.03	0.06	-0.06	-0.03	-0.01	-0.04	1		
	SWC_{t_2}	0.15***	0.02	0.09**	-0.04	-0.02	0.01	0.19***	0.09*	0.28***	0.08*	0.06	0.14***	-0.001	-0.06	1	
	LI_{t_2}	-0.02	0.003	0.16***	-0.18***	0.11**	0.02	0.17***	0.27***	0.16***	0.16***	0.17***	0.03	0.08	-0.04	0.02	1

Notes: CF=Chemical fertilizer, CR=Crop residues, M=Manure, IS=Improved seed, MT=Minimum tillage, LR=Legume rotation, SWC=Soil and water conservation, LI=Legume intercropping. Subscript t_1 = 2009/2010 and t_2 =2012/2013. *, ** and *** are significant at 10%, 5% and 1% level. Standard errors are not reported to conserve space.

Table 3: Coefficient estimates of the dynamic multivariate probit model

Drivers of SAIPs adoption	2009/2010				2012/2013			
	Chemical fertilizer	Crop residues	Manure	Improved seeds	Chemical fertilizer	Crop residues	Manure	Improved seeds
Climate factors								
Rainfall abundance	0.039***	0.045***	0.037***	-0.049***	0.057***	0.043***	-0.007	-0.012
Historical rainfall variability	0.381	6.297***	-3.507*	2.597	6.847***	-2.921	-1.936	1.776
Lagged rainfall variability	-1.609***	-1.274***	0.792***	0.826***	-1.352***	-1.094***	0.138	-0.843***
Temperature variability	-6.373***	3.270*	-1.303	-3.05	-3.245	0.543	0.119	-5.445***
Maximum temperature	0.023	0.058***	0.005	0.064***	-0.014	0.006	0.040**	0.015
Prices								
Fertilizer price	-0.074**	0.099***	-0.001	-0.154***	0.350***	-0.134**	0.125**	0.315***
Improved seed price	0.091***	-0.001	-0.008	0.077***	0.117***	-0.023	-0.002	0.060***
Labour price	-0.036***	0.035***	0.009	-0.026***	-0.083***	0.025	0.000	-0.016
Household socioeconomic characteristics								
Family labour	0.020	-0.008	-0.002	0.054***	-0.029	0.005	0.046***	0.056***
Family education	0.048**	-0.046**	-0.022	0.109***	0.044**	0.01	-0.005	0.023
Education level of head	-0.024*	0.013	0.003	-0.019	-0.050***	0.008	-0.012	-0.030**
Farm size	0.162***	0.090**	0.104**	0.138***	0.320***	0.044	0.144***	0.254***
Ox0	-0.244**	-0.051	-0.268***	-0.108	-0.234**	0.009	-0.239***	-0.310***
Ox1	-0.136*	-0.057	-0.104	-0.083	0.037	-0.201**	-0.051	-0.086
TLU	-0.015**	0.000	0.000	-0.014**	0.000	0.015*	-0.001	-0.017**
Ln asset value	0.066**	0.045	0.011	-0.019	0.073**	0.065**	-0.045*	0.068**
Off-farm cash	-0.352***	0.009	-0.316***	-0.235**	-0.19	-0.076	-0.123	-0.304***
Saving	0.106	0.329***	0.053	-0.051	0.137**	-0.140*	-0.026	0.149**
Credit	0.189**	-0.065	-0.051	0.203**	0.146**	0.004	-0.045	0.001
Gender	-0.005	-0.061	0.183	0.159	0.240*	0.114	-0.252**	0.078
Age	-0.012***	0.004	0.004	-0.012***	-0.016***	-0.010***	-0.001	-0.015***
Farm characteristics								
Soil fertility	0.211***	-0.149**	-0.125**	0.278***	0.058	0.122*	-0.02	0.071

Slope of field	-0.105	0.188***	-0.091	-0.053	0.000	0.180***	-0.118*	-0.154**
Altitude	0.064***	-0.019	0.046***	-0.011	0.080***	0.005	0.020	0.033**
Ln plot distance	0.071**	0.069**	-0.191***	-0.001	0.108***	0.023	-0.158***	0.033
Institutional/Social capital								
Institutions	0.085***	-0.114***	-0.019	0.061***	0.073***	0.007	0.025	0.037**
Ln distance to inputs	-0.080**	0.020	0.030	0.005	-0.105***	-0.067*	0.035	-0.033
Traders	0.012	0.005	0.004	0.012*	-0.002	-0.023**	0.009	-0.003
Relatives	0.000	0.006***	-0.002	0.005**	0.003**	0.001	0.000	0.002
Information	0.109	-0.178**	-0.104	0.053	0.124*	-0.016	-0.045	0.177**
Tenure	-0.099	0.306***	0.027	0.034	0.076	-0.012	0.075	-0.216*
Constant	-0.827	-3.539***	-1.368	-2.761***	-2.484**	-0.706	-0.825	-0.942

Drivers of SAIPs adoption	**2009/2010**				**2012/2013**			
	Minimum tillage	**Legume rotation**	**SWC**	**Legume intercropping**	**Minimum tillage**	**Legume rotation**	**SWC**	**Legume intercropping**
Climate factors								
Rainfall abundance	0.079***	-0.084***	0.056***	-0.004	0.069***	-0.068***	-0.012	0.033**
Historical rainfall variability	6.207**	-6.037**	9.011***	6.660**	0.664	-2.739	-3.083	2.588
Lagged rainfall variability	-0.359	-0.248	0.963***	-3.430***	1.473***	-0.799**	0.477**	-1.350***
Temperature variability	11.006***	1.781	-1.775	-7.275***	3.470	2.257	3.963**	-15.447***
Maximum temperature	-0.011	0.023	-0.041**	0.014	-0.053**	-0.044	-0.018	-0.105***
Prices								
Fertilizer price	0.009	-0.075	-0.079**	0.059	-0.046	-0.072	-0.008	-0.028
Improved seed price	-0.046***	0.002	-0.040***	-0.047***	-0.049*	-0.046*	0.060***	0.012
Labour price	0.021**	0.039***	-0.005	-0.007	0.065***	0.069***	0.040***	-0.077***
Household socioeconomic characteristics								
Family labour	-0.055**	0.049**	-0.017	-0.007	-0.026	0.025	0.012	0.028
Family education	-0.038	0.037	0.026	0.004	-0.016	0.032	0.035*	-0.022
Education level of head	0.044***	0.007	-0.017	0.008	0.043**	0.009	0.007	-0.004
Farm size	0.083*	0.092*	-0.032	0.082	-0.088	0.081	0.052	0.074
Ox0	0.503***	0.085	0.015	0.268**	0.478***	0.001	0.057	0.141
Ox1	0.205**	-0.013	0.139	0.129	0.095	-0.027	0.060	0.013

TLU	-0.011	0.002	-0.006	-0.011	0.001	0.000	0.020***	-0.01
Ln asset value	0.032	-0.033	0.075**	-0.037	-0.028	0.000	-0.015	0.026
Off-farm cash	0.461***	-0.185	-0.309**	-0.225	0.061	-0.047	-0.371***	0.077
Saving	0.049	-0.134	0.115*	0.154*	0.120	-0.199**	0.070	0.09
Credit	0.041	-0.008	-0.054	0.004	0.245***	0.058	0.014	0.071
Gender	-0.151	-0.100	0.071	0.010	-0.071	0.155	0.273**	0.441***
Age	0.014***	-0.007*	-0.008**	0.002	0.011***	-0.005	-0.008***	-0.002
Farm characteristics								
Soil fertility	-0.095	0.052	0.040	0.015	0.046	-0.027	0.098*	-0.038
Slope of field	0.210***	-0.299***	0.361***	-0.004	0.103	0.137	0.421***	0.109
Altitude	-0.176***	-0.034*	0.000	0.026	-0.205***	-0.085***	0.003	-0.011
Ln plot distance	-0.028	0.077**	-0.021	0.073**	-0.047	0.095**	0.053*	-0.068**
Institutional/Social capital								
Institutions	-0.056**	0.052*	0.111***	0.019	-0.057**	0.006	0.048***	-0.011
Ln distance to inputs	0.034	0.009	0.023	0.026	0.037	-0.058	-0.022	0.019
Traders	-0.005	0.007	-0.006	0.006	0.016*	-0.001	0.038***	-0.013*
Relatives	0.002	0.007***	0.001	-0.006*	0.002	-0.003	0.001	0.008***
Information	0.157	0.215**	-0.198**	-0.254**	0.068	0.095	-0.221***	-0.098
Tenure	0.091	0.265**	0.090	0.004	0.057	0.063	0.223*	0.153
Constant	-0.357	0.535	-2.958***	0.633	0.738	2.676*	-1.679*	2.821***

Notes:*, ** and *** are significant at 10%, 5% and 1% probability level. N=2031; log likelihood = -14570.36; Wald χ^2 (496) = 2976.58***; likelihood ratio test of rho χ^2 (120) =1266.46***. To reduce simulation bias, the number of simulation draws (50) was set above the square root of the number observations (Cappellari and Jenkins, 2003). Standard errors are not reported to conserve space.

Table 4: Results of the ordered probit model for the number of sustainable agricultural intensification practices adopted

Technology adoption covariates	Random effects ordered probit		Ordered probit	
	Coefficient	SE	Coefficient	SE
Climate factors				
Rainfall abundance	0.034***	0.008	0.030***	0.007
Historical rainfall variability	1.446	1.260	1.703	1.072
Lagged rainfall variability	-1.119***	0.149	-1.013***	0.129
Temperature variability	-1.570	1.221	-1.444	1.026
Maximum temperature	0.005	0.013	0.005	0.011
Prices				
Fertilizer price	-0.005	0.025	0.002	0.023
Improved seed price	0.029***	0.009	0.029***	0.008
Labour price	-0.002	0.006	-0.002	0.005
Household socioeconomic characteristics				
Family labour	0.026**	0.012	0.022**	0.010
Family education	0.033**	0.013	0.033***	0.011
Education level of head	-0.012	0.008	-0.012*	0.007
Farm size	0.220***	0.030	0.200***	0.026
Ox0	-0.062	0.058	-0.054	0.051
Ox1	-0.022	0.050	-0.025	0.045
TLU	-0.009*	0.005	-0.009**	0.004
Ln asset value	0.045**	0.017	0.040***	0.015
Off-farm cash	-0.369***	0.069	-0.350***	0.062
Saving	0.154***	0.039	0.153***	0.035
Credit	0.088**	0.044	0.072*	0.040
Gender	0.156**	0.080	0.161**	0.068
Age	-0.009***	0.002	-0.009***	0.002
Farm characteristics				
Soil fertility	0.068*	0.034	0.061**	0.031
Slope of field	0.134***	0.039	0.123***	0.035
Altitude	-0.018*	0.010	-0.015*	0.008
Ln plot distance	-0.022	0.017	-0.019	0.015
Institutional/Social capital				
Institutions	0.044***	0.011	0.040***	0.010
Ln distance to inputs	-0.011	0.020	-0.007	0.018
Traders	0.012***	0.004	0.012***	0.004
Relatives	0.004***	0.001	0.004***	0.001
Information	-0.022	0.046	-0.038	0.041
Tenure	0.097	0.063	0.106*	0.057
Time effect				
Year2013	0.461***	0.052	0.426***	0.048
Cuttoff 1	-1.413**	0.569	-1.131	0.482
Cuttoff 2	-0.358	0.568	-0.183	0.481
Cuttoff 3	0.600	0.568	0.679	0.482
Cuttoff 4	1.539***	0.568	1.525	0.482
Cuttoff 5	2.506***	0.568	2.402	0.482
Cuttoff 6	3.524***	0.572	3.324	0.485
Log likelihood	-6320.35		6350.88	
$Sigma^2\_u$	0.230	0.035	Na	
Pseudo R^2	Na		0.052	

Notes:*, ** and *** are significant at 10%, 5% and 1% probability level. Na = not applicable. SE = Standard error. Wald χ^2 (32) = 598.09; Prob> χ^2 =0.000. LR χ^2 (32) = 696.41; Prob > χ^2 = 0.000.

Table 5: Marginal effects of the ordered probit model

Technology Adoption covariates	Number of sustainable agricultural intensification practices adopted						
	Probability $(y_{it}=0\,|\,x_{it})$	Probability $(y_{it}=1\,|\,x_{it})$	Probability $(y_{it}=2\,|\,x_{it})$	Probability $(y_{it}=3\,|\,x_{it})$	Probability $(y_{it}=4\,|\,x_{it})$	Probability $(y_{it}=5\,|\,x_{it})$	Probability $(y_{it}=6\,|\,x_{it})$
Climate factors							
Rainfall abundance	-0.002	-0.006	-0.005	0.003	0.006	0.003	0.001
Historical rainfall variability	-0.081	-0.242	-0.194	0.119	0.254	0.122	0.022
Lagged rainfall variability	0.063	0.187	0.150	-0.092	-0.197	-0.094	-0.017
Temperature variability	0.088	0.262	0.211	-0.129	-0.276	-0.133	-0.023
Maximum temperature	0.000	-0.001	-0.001	0.000	0.001	0.000	0.000
Prices							
Fertilizer price	0.000	0.001	0.001	0.000	-0.001	0.000	0.000
Improved seed price	-0.002	-0.005	-0.004	0.002	0.005	0.002	0.0001
Labour price	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Household socioeconomic characteristics							
Family labour	-0.001	-0.004	-0.003	0.002	0.004	0.002	0.0001
Family education	-0.002	-0.005	-0.004	0.003	0.006	0.003	0.0001
Education level of head	0.001	0.002	0.002	-0.001	-0.002	-0.001	-0.0002
Farm size	-0.012	-0.037	-0.030	0.018	0.039	0.019	0.003
Ox0	0.004	0.010	0.008	-0.005	-0.011	-0.005	-0.001
Ox1	0.001	0.004	0.003	-0.002	-0.004	-0.002	-0.0003
TLU	0.0001	0.001	0.001	-0.001	-0.002	-0.001	-0.0001
Ln asset value	-0.003	-0.007	-0.006	0.004	0.008	0.004	0.001
Off-farm cash	0.021	0.062	0.050	-0.030	-0.065	-0.031	-0.006
Saving	-0.009	-0.026	-0.021	0.013	0.027	0.013	0.002
Credit	-0.005	-0.015	-0.012	0.007	0.016	0.008	0.001
Gender	-0.010	-0.027	-0.019	0.015	0.027	0.012	0.002
Age	0.001	0.002	0.001	-0.001	-0.002	-0.001	-0.0002

Farm characteristics							
Soil fertility	-0.004	-0.011	-0.009	0.006	0.012	0.006	0.001
Slope of field	-0.007	-0.022	-0.018	0.011	0.023	0.011	0.002
Altitude	0.001	0.003	0.002	-0.001	-0.003	-0.002	-0.0003
Ln plot distance	0.001	0.004	0.003	-0.002	-0.004	-0.002	-0.0003
Institutional/Social capital							
Institutions	-0.002	-0.007	-0.006	0.004	0.008	0.004	0.001
Ln distance to inputs	0.001	0.002	0.002	-0.001	-0.002	-0.001	-0.0002
Traders	-0.001	-0.002	-0.002	0.001	0.002	0.001	0.0002
Relatives	0.0001	-0.001	-0.001	0.0001	0.001	0.0001	0.0001
Information	0.001	0.004	0.003	-0.002	-0.004	-0.002	0.000
Tenure	-0.005	-0.016	-0.013	0.008	0.017	0.008	0.001
Time effect							
Year2013	-0.026	-0.076	-0.061	0.037	0.080	0.039	0.007

Notes: Marginal effects (dy / dx) are calculated at the mean for continuous variables and a discrete change from the base for the factor variables. Standard errors are not reported to conserve space.

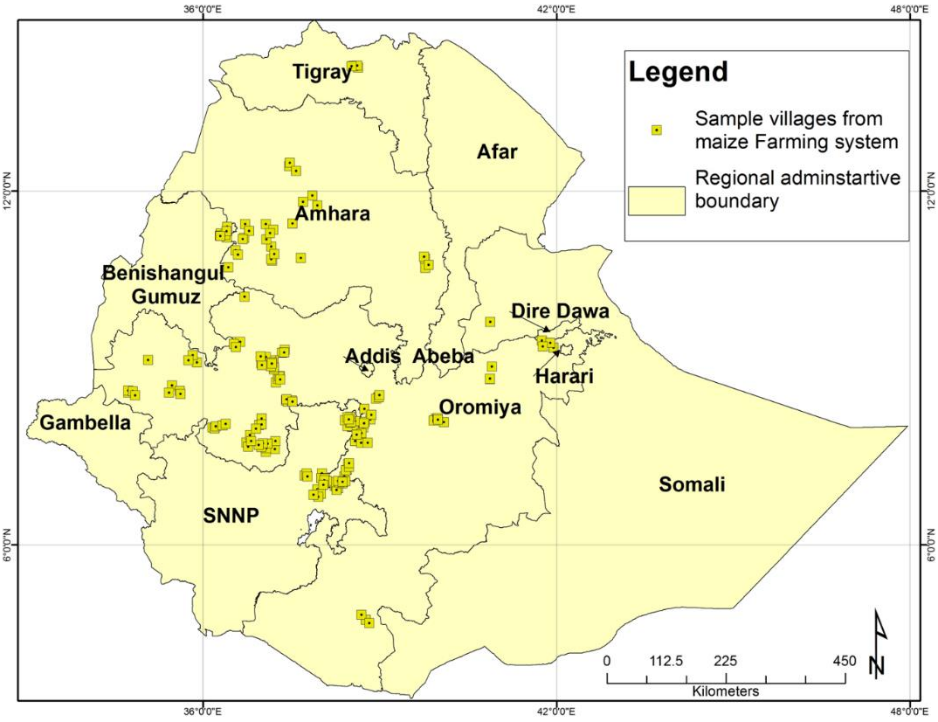

Figure 1: Map of the study villages repressing the major maize growing areas of Ethiopia

References

ABATE, T., SHIFERAW, B., MENKIR, A., WEGARY, D., KEBEDE, Y., TESFAYE, K., KASSIE, M., BOGALE, G., TADESSE, B. & KENO, T. 2015. Factors that transformed maize productivity in Ethiopia. *Food Security,* 7**,** 965-981.

ALEM, Y., BEZABIH, M., KASSIE, M. & ZIKHALI, P. 2010. Does fertilizer use respond to rainfall variability? Panel data evidence from Ethiopia. *Agricultural Economics,* 41**,** 165-175.

ALTIERI, M. A. 2002. Agroecology: the science of natural resource management for poor farmers in marginal environments. *Agriculture, Ecosystems & Environment,* 93**,** 1-24.

ALTIERI, M. A. & TOLEDO, V. M. 2011. The agroecological revolution in Latin America: rescuing nature, ensuring food sovereignty and empowering peasants. *The Journal of Peasant Studies,* 38**,** 587-612.

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.

ARSLAN, A., MCCARTHY, N., LIPPER, L., ASFAW, S., CATTANEO, A. & KOKWE, M. 2015. Climate Smart Agriculture? Assessing the Adaptation Implications in Zambia. *Journal of Agricultural Economics,* 66**,** 753-780.

ASFAW, A. & ADMASSIE, A. 2004. The role of education on the adoption of chemical fertiliser under different socioeconomic environments in Ethiopia. *Agricultural Economics,* 30**,** 215-228.

ASFAW, S., DI BATTISTA, F. & LIPPER, L. 2016. Agricultural Technology Adoption under Climate Change in the Sahel: Micro-evidence from Niger. *Journal of African Economies,* 25**,** 637-669.

BAUDRON, F., SIMS, B., JUSTICE, S., KAHAN, D. G., ROSE, R., MKOMWA, S., KAUMBUTHO, P., SARIAH, J., NAZARE, R., MOGES, G. & GÉRARD, B. 2015. Re-examining appropriate mechanization in Eastern and Southern Africa: two-wheel tractors, conservation agriculture, and private sector involvement. *Food Security,* 7**,** 889-904.

BECERRIL, J. & ABDULAI, A. 2010. The Impact of Improved Maize Varieties on Poverty in Mexico: A Propensity Score-Matching Approach. *World Development,* 38**,** 1024-1035.

BEZABIH, M. & SARR, M. 2012. Risk Preferences and Environmental Uncertainty: Implications for Crop Diversification Decisions in Ethiopia. *Environmental and Resource Economics,* 53**,** 483-505.

BORLAUG, N. 2007. Feeding a Hungry World. *Science,* 318**,** 359-359.

CAPPELLARI, L. & JENKINS, S. P. 2003. Multivariate probit regression using simulated maximum likelihood. *Stata Journal,* 3**,** 278–294.

CHAVAS, J.-P., PETRIE, R. & ROTH, M. 2005. Farm Household Production Efficiency: Evidence from The Gambia. *American Journal of Agricultural Economics,* 87**,** 160-179.

DE SCHUTTER, O. & VANLOQUEREN, G. 2011. The new green revolution: How twenty-first-century science can feed the world. *Solutions,* 2**,** 33–44.

DI FALCO, S. 2014. Adaptation to climate change in Sub-Saharan agriculture: assessing the evidence and rethinking the drivers. *European Review of Agricultural Economics,* 41**,** 405-430.

DI FALCO, S. & VERONESI, M. 2014. Managing Environmental Risk in Presence of Climate Change: The Role of Adaptation in the Nile Basin of Ethiopia. *Environmental and Resource Economics,* 57**,** 553-577.

DORFMAN, J. H. 1996. Modeling Multiple Adoption Decisions in a Joint Framework. *American Journal of Agricultural Economics,* 78**,** 547-557.

DOSS, C. R. 2006. Analyzing technology adoption using microstudies: limitations, challenges, and opportunities for improvement. *Agricultural Economics,* 34**,** 207-219.

FAO 2007. *State of Food and Agriculture 2008: Paying Farmers for Enviromental Services. Food and Agriculture Organization of the United Nations,* Rome.

FEDER, G., JUST, R. E. & ZILBERMAN, D. C. F. P. D. J. 1985. Adoption of Agricultural Innovations in Developing Countries: A Survey. *Economic Development and Cultural Change,* 33**,** 255-298.

GEBREMEDHIN, B. & SWINTON, S. M. 2003. Investment in soil conservation in northern Ethiopia: the role of land tenure security and public programs. *Agricultural Economics,* 29**,** 69-84.

GOLLIN, D., MORRIS, M. & BYERLEE, D. 2005. Technology Adoption in Intensive Post-Green Revolution Systems. *American Journal of Agricultural Economics,* 87**,** 1310-1316.

GREENE, W. H. 2016. NLOGIT Version 6: user's manual reference guide. Econometric Software, Inc. . New York: Econometric Software, Inc.

HAGGBLADE, S., HAZELL, P. & BROWN, J. 1989. Farm-nonfarm linkages in rural sub-Saharan Africa. *World Development,* 17**,** 1173-1201.

HELLERSTEIN, D., GREENE, C. & BOWMAN, M. 2017. Symphony of the Soil [documentary]. Directed, produced, and written by Deborah Koons. *American Journal of Agricultural Economics,* 99**,** 840-842.

HOBBS, P. R., SAYRE, K. & GUPTA, R. 2008. The role of conservation agriculture in sustainable agriculture. *Philosophical Transactions of the Royal Society B: Biological Sciences,* 363**,** 543-555.

KAHNEMAN, D. & TVERSKY, A. 1979. Prospect Theory: An Analysis of Decision under Risk. *Econometrica,* 47**,** 263-291.

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**,** 525-540.

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.

KASSIE, M., ZIKHALI, P., PENDER, J. & KOHLIN, G. 2010. The Economics of Sustainable Land Management Practices in the Ethiopian Highlands. *Journal of Agricultural Economics,* 61**,** 605-627.

KATHAGE, J., KASSIE, M., SHIFERAW, B. & QAIM, M. 2016. Big Constraints or Small Returns? Explaining Nonadoption of Hybrid Maize in Tanzania. *Applied Economic Perspectives and Policy,* 38**,** 113-131.

KNOWLER, D. & BRADSHAW, B. 2007. Farmers' adoption of conservation agriculture: A review and synthesis of recent research. *Food Policy,* 32**,** 25-48.

KOPPMAIR, S., KASSIE, M. & QAIM, M. 2017. The influence of farm input subsidies on the adoption of natural resource management technologies. *Australian Journal of Agricultural and Resource Economics,* 61**,** 539-556.

LAMBRECHT, I., VANLAUWE, B., MERCKX, R. & MAERTENS, M. 2014. Understanding the Process of Agricultural Technology Adoption: Mineral Fertilizer in Eastern DR Congo. *World Development,* 59**,** 132-146.

LEE DAVID, R., BARRETT CHRISTOPHER, B. & MCPEAK JOHN, G. 2006. Policy, technology, and management strategies for achieving sustainable agricultural intensification. *Agricultural Economics,* 34**,** 123-127.

LEE, D. R. 2005. Agricultural Sustainability and Technology Adoption: Issues and Policies for Developing Countries. *American Journal of Agricultural Economics,* 87**,** 1325-1334.

MARENYA, P. P. & BARRETT, C. B. 2007. Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western Kenya. *Food Policy,* 32**,** 515-536.

MELINDA, S. & JOHN, O. 2014. Demand for maize hybrids and hybrid change on smallholder farms in Kenya. *Agricultural Economics,* 45**,** 409-420.

NDLOVU, P. V., MAZVIMAVI, K., AN, H. & MURENDO, C. 2014. Productivity and efficiency analysis of maize under conservation agriculture in Zimbabwe. *Agricultural Systems,* 124**,** 21-31.

PINGALI, P. 2007. Agricultural growth and economic development: a view through the globalization lens. *Agricultural Economics,* 37**,** 1-12.
SESMERO, J., RICKER-GILBERT, J. & COOK, A. 2018. How Do African Farm Households Respond to Changes in Current and Past Weather Patterns? A Structural Panel Data Analysis from Malawi. *American Journal of Agricultural Economics,* 100**,** 115-144.
SHIFERAW, B. & HOLDEN, S. T. 2000. Policy instruments for sustainable land management: the case of highland smallholders in Ethiopia. *Agricultural Economics,* 22**,** 217-232.
STEVENSON, J. R., SERRAJ, R. & CASSMAN, K. G. 2014. Evaluating conservation agriculture for small-scale farmers in Sub-Saharan Africa and South Asia. *Agriculture, Ecosystems & Environment,* 187**,** 1-10.
STEVENSON, J. R., VILLORIA, N., BYERLEE, D., KELLEY, T. & MAREDIA, M. 2013. Green Revolution research saved an estimated 18 to 27 million hectares from being brought into agricultural production. *Proceedings of the National Academy of Sciences,* 110**,** 8363-8368.
TEKLEWOLD, H., KASSIE, M. & SHIFERAW, B. 2013. Adoption of Multiple Sustainable Agricultural Practices in Rural Ethiopia. *Journal of Agricultural Economics,* 64**,** 597-623.
TEKLEWOLD, H., MEKONNEN, A., KOHLIN, G. & DI FALCO, S. 2017. DOES ADOPTION OF MULTIPLE CLIMATE-SMART PRACTICES IMPROVE FARMERS' CLIMATE RESILIENCE? EMPIRICAL EVIDENCE FROM THE NILE BASIN OF ETHIOPIA. *Climate Change Economics,* 08**,** 1750001.
TEMESGEN, M., HOOGMOED, W. B., ROCKSTROM, J. & SAVENIJE, H. H. G. 2009. Conservation tillage implements and systems for smallholder farmers in semi-arid Ethiopia. *Soil and Tillage Research,* 104**,** 185-191.
THE MONTPELLIER PANEL 2013. Sustainable Intensification: A New Paradigm for African Agriculture. London.
UDRY, C. 1996. Gender, Agricultural Production, and the Theory of the Household. *Journal of Political Economy,* 104**,** 1010-1046.
VON NEUMANN, J. & MORGENSTERN, O. 1947. *Theory of games and economic behavior (2d rev. ed.),* Princeton, NJ, US, Princeton University Press.
WAINAINA, P., TONGRUKSAWATTANA, S. & QAIM, M. 2016. Tradeoffs and complementarities in the adoption of improved seeds, fertilizer, and natural resource management technologies in Kenya. *Agricultural Economics,* 47**,** 351-362.
WOLLNI, M., LEE, D. R. & THIES, J. E. 2010. Conservation agriculture, organic marketing, and collective action in the Honduran hillsides. *Agricultural Economics,* 41**,** 373-384.
WORLD BANK 2008. Agriculture for Development. World Development Report 2008. Washington, DC.