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Pathways from information to the adoption of conservation agriculture practices in Malawi and Tanzania

Paswel P. Marenya[1], Josephine G. Gatua[2] and Dil B. Rahut[3]

[1]International Maize and Wheat Improvement Center (CIMMYT), P.O. Box 1041-00621, Nairobi, Kenya; [2]University of Gothenburg, Gothenburg, Sweden and [3]Asian Development Bank Institute, Tokyo, Japan

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Corresponding author:
Paswel P. Marenya;
Email: p.marenya@cgiar.org

Abstract

To reduce agriculture's carbon, land and water footprint, the diffusion of conservation farming methods is one commonly cited proposition. Yet the process of translating available information on new conservation farming methods into farmers' practices is often a black box in many studies. This understanding is critical to inform strategies for scaling these complex, knowledge-intensive, but necessary practices for improving agriculture's resource and climate balance sheet. By implementing a series of mediation analysis using data from 700 households in Malawi and 930 households in Tanzania, this study examines how an improved understanding of conservation agriculture (CA) principles is an important mediator in the pathway from extension contact to the adoption of two of the CA practices examined. For the adoption of conservation tillage, the share of the mediated treatment effect was in the 31.5–34.4% range, while it was 31.6–46.9% for the adoption of soil cover (mulching). Our results suggest that unless learning from external sources strongly correlates with improved farmers' technical understanding of new farming practices, private learning by doing must be a critical adjunct to other avenues of learning. Beyond the basic promotional goals, improving farmers' technical know-how needs to be the centerpiece of holistic efforts in support of conservation farming and similar knowledge-intensive practices necessary for agriculture's sustainability goals.

Introduction

To reduce agriculture's carbon, land and water footprint, the diffusion of conservation farming methods is one important proposition. Although not new in some parts of the world (e.g., Argentina, Brazil, USA), conservation agriculture (CA) has emerged in recent years as a paradigm shift in agronomy in smallholder agriculture. It has attracted the attention of agronomists, economists and development practitioners. CA is often defined as a suite of practices that, when applied together, can increase yields and preserve agricultural resources (Hobbs *et al*., 2008; FAO, 2012). The full set of practices is usually characterized by minimizing soil disturbance, maintaining soil cover (SC), practicing crop rotation and intercropping. In broad terms, although CA promises to conserve resources and raise yields, the evidence base from socio-economic, policy and institutional enablers of its diffusion has lagged the agronomic advancements (Giller *et al*., 2009). As expected, factors such as perceptions of risk, uncertainty, the need for farmers' own experimentation and the related learning costs are likely to be relevant to the adoption of CA. Other factors related to input prices, knowledge, scarcity of labor, lack of capital, farm size and poor infrastructure have been suggested as factors that influence the adoption of CA (Nyamangara *et al*., 2014). In terms of positive drivers of adoption, the reduced cost of operations (mainly tillage) is often cited, especially if weed management is performed with herbicides (Fowler and Rockstrom, 2001; Erenstein *et al*., 2012). While the evidence is mixed, some yield increases are possible in well-managed CA systems (Giller *et al*., 2009). Therefore, the multiple components of CA (zero/reduced tillage, crop diversification and mulching) that need to be applied simultaneously imply an information-intensive process of adoption that require farmers to learn over a period of time.

Farmers can learn and adopt new CA solutions through a multi-season process of *exposure to information* (Khainga *et al*., 2021) followed or accompanied by *hands-on experimentation* (Maertens *et al*., 2021; Marenya and Usman, 2021), and Bayesian updating (Leathers and Smale, 1991). In tandem, they could also learn from others in their social networks. Such *social learning* only happens if the farms, soils and socio-economic circumstances mirror their own (Foster and Rosenzweig, 1995; Ben Yishay and Mobarak, 2013). In other cases, *trusted social influencers* such as lead farmers or other respected community members who are *exemplar farmers* can facilitate information delivery and learning where trust is important for farmers to emulate lead adopters (Ben Yishay and Mobarak, 2013).

A combination of social and private learning will likely be needed in many cases. This is because complex agronomic practices, such as CA, require multi-season observations and need to be tailored to individual resource conditions for successful implementation. Social learning occurs when, by observing what neighbors and others in their physical and social proximity are doing, farmers by imitation or emulation learn about new farming practices. Private learning occurs through own efforts to privately acquire information from any number of sources and through on-farm trial and adaption, farmers learn about new practices and innovations.

Consistent with the need for hands-on experiences, Maertens *et al.* (2021) show that first-hand and local experiences appear more important than other passive extension approaches in shaping farmers' expectations of the performance (and the likelihood of adoption) of integrated soil fertility management practices. Although Conley and Udry (2010) found evidence that farmers adopt newly introduced agronomic packages for pineapple growing in Ghana, this is conditional on common growing conditions and other factors, suggesting limits to learning from social networks. A subtle point is made by Ben Yishay and Mobarak (2019), who found that local farmers acting as injection points in local social networks can be incentivized to properly demonstrate new agriculture practices and better influence their neighbors with whom they share similar social identity and growing conditions. However, in many cases, information on the actions of neighbors is difficult to observe (see Munshi, 2004; Tjernstrom, 2016), making it challenging to use observed outcomes to inform adoption decisions. We raise these issues not to discount the importance of learning through social networks but rather to highlight the need to regard social learning platforms as part of farmers learning ecosystems.

To help in highlighting this issue in ways that (to the best of our knowledge) have not been done in the previous literature, this paper strives to identify the effectiveness of extension approaches in achieving a level of understanding of CA that can promote its widespread adoption. This paper contributes to the literature by helping answer one of the central questions of the effectiveness of agricultural extension: Do interactions with extension agents, development projects and the like deliver the quality of learning needed to promote the self-sustaining adoption of complex multi-component technologies such as CA? This is a crucial question the world over but particularly in low-income country agriculture (where agricultural development still lags). The CA example lends itself to this kind of analysis because of the abstract nature of learning from extension agents or external social networks. Few studies in the large repository of literature adequately explain how information is mediated to affect the adoption process, our paper aims to fill part of this gap.

This paper therefore advances the agricultural research and development discourse by examining how three different extension approaches (demonstrations, farmer field schools and field days) lead to the adoption of CA components involving conservation tillage (CT) and SC or mulching. The use of these extension approaches is premised on their positive effects on the adoption of CA. Yet the aspect of how this process is mediated has not been studied well in the literature. We answer this question by testing the mediation effects emanating from an accurate understanding of CA principles on the probability of adopting CT and SC among smallholder farmers in Malawi and Tanzania. We define an accurate understanding of CA as the respondent's ability to define CA as involving the application of all three principles of CT, SC and crop rotations. We use this measure to proxy for the quality of learning that was achieved from contact with the three extension modalities. This indicative accurate understanding is used as a potential mediating factor between extension contact and adoption.

Data sources and sampling

The data for this study were derived from a multiyear, multidisciplinary project that focused on agronomic testing and the extension of CA practices appropriate for smallholders. The field implementation of the project ended in mid-2018, and the data were collected in October–December 2018. The purpose was to provide end-of-project information on project performance. The project itself had been implemented since 2009 and by 2018, was in its ninth year. This paper contributed to this process by analyzing the impact of project extension activities on the adoption of CA practices. A continuous random sampling procedure was used in the two project countries (Malawi and Tanzania). A two-stage approach was used in the sampling process. In the first stage, we selected the primary sampling units (PSUs) in each country. The PSUs were the lower-most administrative units within which the project was implemented. Within the PSUs, households were randomly selected as units for analysis. The project-related activities were performed at nucleus demonstration and training sites in different project locations spread across the implementation sites. Selected sites hosted demonstration plots in each season during the implementation, supplemented by formal farmers' field days and training sessions. Each site served several villages depending on population and infrastructure. The study was therefore limited to the PSUs that were within a 17–20 km radius of the demonstration plots. The choice of the 17–20 km radius was based in focus group discussions and the fact that the project had been implemented in these areas for almost a decade (9 years). Moreover, this radius fitted within what an extension officer would be assigned to in these areas. Based on this reasoning, we considered such a radius as a reasonable zone of influence. Within that radius, households were selected from villages in the PSUs by a continuous random sampling process. Care was taken to exclude the farmers who hosted project demonstration sites from the survey sample because they could not be considered unbiased adopters. We therefore excluded these farmers' data from the analysis because they are not a random selection of adopting and non-adopting farmers. Often farmers who host demonstrations are not randomly selected but are chosen through community discussions in conjunction with scientists to achieve some spatial and social heterogeneity. Given that the final sample was drawn randomly, we excluded the farmers hosting the demonstrations.

The study received help from local agricultural extension officers and village managers to prepare complete lists of households in each village from which the sample could be chosen. The process was conducted by a team of extension staff and village leaders who knew these villages well. The village leaders often already maintain a list going village by village, which are small units and it is not a very big task to generate a full listing of all homesteads and households in the village.

The map in Figure 1 below shows the locations and numbers of selected households that participated in the survey. The sample size for each country was determined following a formula similar to those used by Kristein (2012):

$$n = \frac{4\sigma^2(z_{1-\alpha/2} + z^2_{1-\beta)}}{D^2}[1 + \rho(m-1)]$$

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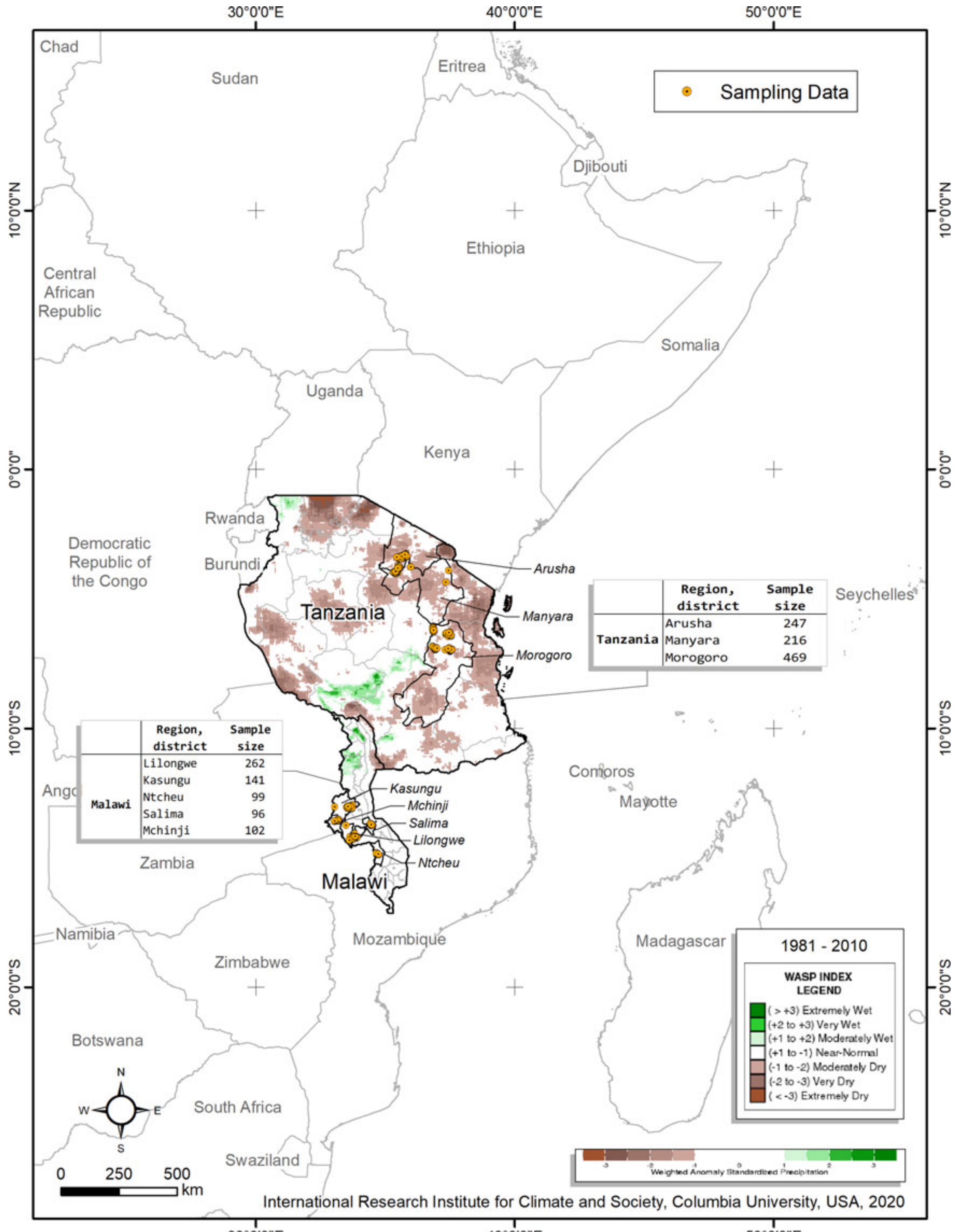

Figure 1. Study locations in Malawi and Tanzania.

where n = sample size; σ = variance in population outcome metric; D = the effect size or how much of an impact the project would have; $Z_{1-\alpha} = Z$ value at 5% significance level/probability of type 1 error; $Z_{1-\beta} = Z$ value at 80% statistical power/probability of type 2 error; ρ = the intracluster correlation effect; m = the number of observations in each cluster (village).

The above formula generated a sample size of 700 households in Malawi and 930 in Tanzania. The data cleaning processes meant that the final sample sizes used in the regression models might vary slightly. A structured questionnaire was used to elicit responses and capture data on key household demographics, such as education, the number of household members and the head of the household. Additionally, we collected plot-level data of maize plots about the practices and inputs used. These data were used in the estimation models described in the next section.

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Model estimation framework

Our main interest lies in understanding the contribution of extension-acquired knowledge to the adoption of CA practices. We used mediation analysis to determine whether and to what extent the adoption effect of participating in project activities was mediated through the resulting higher-quality knowledge of CA. Treatment assignment was defined by three variables: (i) whether the farmer visited a demonstration site on an individual basis (hereafter, demonstration); (ii) whether the farmer attended structured class/field training (hereafter, training) and (iii) whether the farmer attended organized communal farmer field days. As has often been recognized in the literature, the farmers who attended various extension activities in our sample constituted a somehat self-selectng sample. This is because it is likely that those who took the initiative to come to any of the three sessions have characteristics that increased their attendance to these extension sites and events. Therefore, these groups could be a skewed social or economic class in ways we did not or could not observe. Hence, in estimating the mediation effect of interest, we must take into account the possible selection bias in the data. As we explain later, we account for selection bias by using propensity score matching (PSM). This means that our comparison groups have similar propensity scores (are statistically similar) First, we briefly expound on the mediation phenomenon that we used.

A mediating factor helps to explain how a treatment variable works (Vlaeyen and Morley, 2005). This is equivalent to confirming the hypothesized working mechanism underlying an intervention. Using the random utility framework, consider the i^{th} farm adopter ($i = 1\ldots N$) facing the decision of whether to adopt the available CA practice on plot P ($P = 1, \ldots, P$). Let U_0 represent the benefits to the farmer from traditional management practices (MP), and let U_k represent the benefit of adopting the k^{th} MP, where k denotes the choice of a CA practice. The farmer decides to adopt the k^{th} MP on plot P if $Y_{ipk} = U_k - U_0 > 0$. The perceived net benefit of adopting any MP is influenced by *how well the farmer understands and implements* the various aspects of the MP in question. This is important because implementing the MP accurately as per the recommendation ensures cost-effectiveness, and proven cost-effectiveness would sustain adoption. For the successful implementation of MP, farmers need to internalize the principles of MP in the process of evaluating and trying it on their farms. Therefore, the channel we test is whether farmers' knowledge of MP directly affects the decision to adopt CA practices. This provides the basis for the choice of the outcome and mediating variables. The intervention may translate into better knowledge about MPs in general, thereby increasing its adoption.

Let Y_i represent an outcome variable (adoption of an MP), T_i is the treatment, X_i denotes control variables and M_i is the mediator. Mediation analysis can be conducted by estimating the equations:

$$M_i = \alpha_1 + \beta_1 T_i + \gamma_1 X_i + \epsilon_{1i} \tag{1}$$

$$Y_i = \alpha_2 + \beta_2 T_i + \gamma_2 X_i + \sigma_2 M_i + \epsilon_{1i}. \tag{2}$$

For the empirical estimation of Equations (1) and (2) to represent a causal mediation analysis, the following conditions should be satisfied: (i) predictor T (treatment) should be causally related to outcome Y before mediator M is added to the model, (ii) T should be causally related to M and (iii) M should be causally related to Y when controlling for T.

The first two conditions assume the exogeneity of the treatment T to Y and M (random assignment of the treatment). In observational studies, treatments are not randomized, which makes it difficult to satisfy the exogeneity assumption. Conditional on using PSM or the Heckman selection model, we can mimic the random treatment assignment, which implies that the average treatment effect is identified. However, calculating the average treatment effect occurring through a mediation variable M_i (T_i), which is also affected by the treatment, requires additional assumptions. The third condition is the exogeneity assumption of the mediator, which states that once we condition on T_i, the mediator should be exogenous. This assumption implies that the effects of unmeasured covariates that confound the relationship between the mediator and the dependent variable have been removed.

To understand why an intervention affects an outcome, we turn to the causal mechanism framework. We follow the reasoning on causal mechanisms by Imai *et al.* (2011). The causal effect of treatment might flow through another intermediate variable on the causal pathway from treatment to outcome. The causal pathway is an indirect or mediated effect, which tells us how the effect of the treatment depends on a particular pathway. To define the key quantities of interest in our causal mediation analysis, we rely on the potential outcome framework for causal inference (Rubin, 1974). Assuming all three assumptions stated above are satisfied, the estimates from Equations (1) and (2) can be used to estimate the causal true parameters. Therefore, β_1 denotes the effect of the treatment on the mediator, while σ_2 is the effect of the mediator on the outcome. Thus, the average causal mediation effect (ACME) is computed as $\sigma_2\beta_1$. For ACME to hold, the sequential ignorability assumption implies that the correlation between the two error terms ϵ_{1i} and ϵ_{2i} is zero. The above equations are estimated assuming this zero correlation between the error terms. Note that β_2 represents the average direct effect (ADE). The average treatment effect (ATE), which represents the effect of the treatment on the outcome variable, can be decomposed into the sum of ACME and ADE (i.e., ATE = ACME + ADE). Given the importance of testing the validity of the sequential ignorability assumption, we use the sensitivity analysis developed by Imai *et al.* (2011) to determine if our assumption of sequential ignorability is defensible.

Variables used in the mediation models

Dependent (outcome) variables

This study focused on explaining the adoption of two elements of CA, namely, the area under *conservation tillage* (previously denoted as CT) and the area under soil cover (previously denoted as SC). These constitute the basic outcome variables. CT was defined as the practice of opening only seeding holes to plant the seed without tilling the plot. In the use of CT, weeding was mechanically accomplished by shallow weeding (chopping off the weeds at above-ground level or by very shallow digging) or spraying with a herbicide. The use of SC was defined as the application of crop residues (mainly those of maize) as mulch for weed suppression and moisture conservation by forming a protective cover on the surface. The two practices were selected to represent

Table 1. Summary statistics (Malawi and Tanzania)

	Malawi			Tanzania			Expected sign
Variable	*N*	Mean	SD	*N*	Mean	SD	
Outcome-adoption-plot level (currently practicing)							
At end of project (2018)							
Conservation tillage (yes = 1)	1899	0.11	0.31				
Area under conservation tillage (ha)	1894	0.05	0.19				
Soil cover (yes = 1)	1947	0.24	0.43	1505	0.04	0.19	
Area under soil cover (ha)	1921	0.1	0.25	1486	0.04	0.27	
Adoption at start of project (2009)							
Conservation tillage (yes = 1)	700	0.05	0.03	930	0.001	0.005	
Soil cover (yes = 1)	700	0.012	0.01	930	0.006	0.03	
Treatment variables-HH level, Have you participated in SIMLESA activities (for the whole sample)							
Visited demonstration sites	700	0.42	0.49	930	0.2	0.4	**+**
Attended field days	699	0.36	0.48	930	0.17	0.38	**+**
Participated in trainings on CA	699	0.36	0.48	930	0.1	0.31	**+**
Explanatory variables							
Total number of household members	700	5.69	5.57	931	5.96	2.36	–
Sex of the household head (male = 1)	700	0.83	0.38	931	0.85	0.36	+
Age (completed years)	700	45.22	13.59	931	48.04	10.98	+
Education of the HH (years)	700	6.01	3.55	931	6.95	2.33	+
Education of the HH spouse (years)	571	5.16	3.1	748	6.72	2.11	+
Nearest major trading center in (km)	700	7.11	7.63	930	7.75	10.28	±
Nearest farmers' cooperative seed warehouse/farm inputs in (km)	699	6.62	8.89	930	10.85	11.21	±
Total plot size (ha.)	696	1.11	0.94	932	1.55	2.89	+
Total no. of livestock (household level)	700	8.99	76.72	932	19.78	21.06	+
Plot level explanatory variables							
Plot distance from residence (walking minutes)	1922	23.3	24.72	1484	30.51	42.36	–
Sub-plot size (ha)	1924	0.4	0.35	1487	0.97	1.32	+
Location dummies (counties in Malawi and Tanzania, respectively)							
Lilongwe	262	37.43					±
Kasungu	141	20.14					±
Ntcheu	99	14.14					±
Salima	96	13.71					±
Mchinji	102	14.57					±
Arusha				247	26.5		±
Manyara				216	23.18		±
Morogoro				469	50.32		±
		Percent			Percent		
Mediator variable-HH level of CA understanding (score of the farmer's understanding of CA)							
Incorrect [no mention of CA]	106	15.14		628	67.45		–
Partially correct [mention at least two]	381	54.43		188	20.19		+
Correct [mentions combination of the 3 CA]	213	30.43		115	12.35		+
Total	700	100		931	100		

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Table 2. Effect of visiting demonstration sites on adoption of conservation tillage in Malawi

	Malawi		
	(1)	(2)	(3)
Panel A: effect of treatment and mediator on adoption			
Visited demonstration sites	0.028***	0.025***	0.028***
	(0.009)	(0.009)	(0.009)
Accurate understanding of CA	0.045***	0.043***	0.034***
	(0.009)	(0.009)	(0.009)
Household size		−0.001	−0.001
		(0.001)	(0.001)
Sex		0.017	0.015
		(0.012)	(0.012)
Age		0.001***	0.002***
		(0.000)	(0.000)
Trading center (km)		0.001**	0.001**
		(0.001)	(0.001)
Observations	2040	2033	2033
R^2	0.025	0.041	0.057
Panel B: estimate of ACME and ADE			
Treatment effect on accurate understanding of CA	0.954***	0.942***	0.971***
	(0.060)	(0.061)	(0.063)
ACME	0.014	0.014	0.012
ADE	0.029	0.025	0.027
% of treatment effect mediated	32.5	36.7	29.9
Additional covariates	No	Yes	Yes
Location fixed effects	No	No	Yes

Standard errors in parentheses ***$P<0.01$, **$P<0.05$, *$P<0.1$. The share of treatment effect is the % of total mediated effect × 100.

Table 3. Effect of attending field days on adoption of conservation tillage in Malawi

	Malawi		
	(1)	(2)	(3)
Panel A: effect of treatment and mediator on adoption			
Attended field days	0.027***	0.027***	0.026***
	(0.009)	(0.009)	(0.009)
Accurate understanding of CA	0.046***	0.043***	0.035***
	(0.009)	(0.009)	(0.009)
Household size		−0.002	−0.001
		(0.001)	(0.001)
Sex		0.018	0.016
		(0.012)	(0.012)
Age		0.002***	0.002***
		(0.000)	(0.000)
Trading center (km)		0.001**	0.001**
		(0.001)	(0.001)
Observations	2037	2030	2030
R^2	0.024	0.042	0.056
Panel B: estimate of ACME and ADE			
Treatment effect on accurate understanding of CA	0.924***	0.920***	0.907***
	0.060	0.060	0.061
ACME	0.014	0.015	0.012
ADE	0.028	0.027	0.026
% of treatment effect mediated	34.4	35.0	31.5
Additional covariates	No	Yes	Yes
Location fixed effects	No	No	Yes

Standard errors in parentheses ***$P<0.01$, **$P<0.05$, *$P<0.1$.
Share of treatment effect is the % of total mediated effect × 100.

the two most critical aspects of CA, without which CA systems would not succeed. These two elements are also the most novel (especially CT) and require the most improvement in know-how. Although crop rotation and intercropping are part of CA, we did not include them in the analysis because they have been part of the farming system and are widely adopted before CA was promoted in these communities. When combined with crop rotation and intercropping the three (CT, CA and intercropping/rotations) will constitute CA. Therefore, the adoption of CT and SC provides an appropriate case for how adoption is mediated by improved know-how arising from information exposure to the innovation.

During the household interviews, each respondent was asked to provide information on the use of CA and other practices on all their maize sub-plots. A sub-plot was defined as a contiguous patch of land on which maize was grown as the primary crop (solely maize, in rotation or intercropped with any legume) and using a particular MP. For each sub-plot, we obtained information regarding the practices used to grow maize, including whether the sub-plot was managed using any CA component practices: whether CT or normal tillage was used, in addition to whether SC (mulching) was used and other practices. The respondent was asked to estimate the size of each sub-plot and what portion was managed under any of the CA practices, and these areas were standardized to hectare equivalents.

Treatment variables

The treatment variables considered were exposure to the project extension (scaling) activities. Recall that the project implemented a mix of approaches to promote CA practices among the

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Table 4. Effect of training on CA on adoption of conservation tillage in Malawi

	Malawi		
	(1)	(2)	(3)
Panel A: effect of treatment and mediator on adoption			
Attended training sessions on CA	0.040***	0.036***	0.038***
	(0.009)	(0.009)	(0.009)
Accurate understanding of CA	0.042***	0.040***	0.032***
	(0.009)	(0.009)	(0.009)
Household size		−0.002*	−0.002
		(0.001)	(0.001)
Sex		0.020*	0.018
		(0.012)	(0.012)
Age		0.001***	0.001***
		(0.000)	(0.000)
Trading center (km)		0.001**	0.001**
		(0.001)	(0.001)
Observations	2036	2029	2029
R^2	0.032	0.049	0.067
Panel B: estimate of ACME and ADE			
Treatment effect on accurate understanding of CA	0.939***	0.950***	0.984***
	0.060	0.061	0.063
ACME	0.014	0.014	0.011
ADE	0.041	0.036	0.038
% of treatment effect mediated	25.0	28.5	23.2
Additional covariates	No	Yes	Yes
Location fixed effects	No	No	Yes

Standard errors in parentheses ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

communities around the demonstration sites. The three main extension methods were: individual (informal) visits to CA demonstration sites, organized formal farmer field days and in-class and field-based training sessions on CA and related aspects. The project field teams organized demonstrations in high-visibility areas to showcase CA farming techniques. These demonstration sites were locations along major village roads, near public facilities such as markets and religious compounds, and government offices. While the demonstrations were meant to 'speak for themselves', the project teams also organized field days for the community to interact with the extension and project staff. The final aspect was the hands-on training sessions on CA practices. The data (presented later) show variation in the number of times any individual participated in the different activities. Project teams implemented the activities in collaboration with local extension staff, farmer community groups and other nonprofit community development organizations. This multi-stakeholder approach was intended to help mobilize and capitalize on the convening capacity of grassroots organizations. Over a period spanning approximately 7–8 growing seasons, project teams implemented these three methods to deliver the information by asking farmers to observe the CA demonstration by visiting the demonstration sites, attending training and field days and trying the new methods on their farms.

Mediation variable

The basic notion behind the mediation variable is that exposure to demonstrations, field days and training will promote the adoption of CT, SC and related components by improving farmers' technical understanding of CA. A question was asked to let all respondents describe what they understood as CA. The interviewer took note of whether the respondent described something but mentioned none of the three principles (minimum/zero tillage, mulching and crop diversification by rotations or intercropping), or the respondent acknowledged a complete lack of awareness. Therefore, each farmer's response was categorized as (a) no information or knowledge (as above), (b) they described CA but fell short of listing all three principles, mentioning a maximum of two of the three principles (this category was described as having partial or incomplete knowledge of CA), and (c) they mentioned all three elements in their description; these farmers were categorized as having accurate or complete knowledge of CA. In constructing the mediation indicator variable, we categorized farmers into two: those who had accurate (complete) knowledge of CA and those who had only partial or no knowledge.

Other covariates

Finally, other covariates were used in the regression models. These control variables included the total number of members in a household and demographics of the household head and spouse (sex, age, years of education and years of education). Institutional (community) variables included the distance of the residence from the nearest major trading center and distance to the nearest farm input sales point in kilometers. As described above, farm-level covariates included the total area of all plots cultivated under maize and other associated crops (ha.), number of livestock owned, distance from residence to the plot and the plot size on which CA was implemented.

Results

Descriptive statistics

Table 1 summarizes the descriptive statistics from the samples described above. Participation in demonstrations, field days and training was 20, 17 and 10%, respectively, in Tanzania and 42, 36 and 36%, respectively, in Malawi. CT was adopted on 11% of the plots in Malawi. The adoption of SC was 24% in Malawi and 4% in Tanzania. The demographics suggested relatively low levels of education for the household heads, with 6.0 and 7.0 years in Malawi and Tanzania, respectively. The respondents' spouses had been educated for 5.2 and 6.7 years, respectively. Overall, 83% (Malawi) and 85% (Tanzania) of the households were headed by males. Their total cultivated maize plots were 1.1 ha (Malawi) and 1.6 ha (Tanzania) on average. Access to trading centers or input outlets was approximately 9 km in Malawi and 11 km in Tanzania. On average, the farmers lived within walking distances of 23 min (Malawi) and 31 min (Tanzania) from their plots. The percentage of farmers who correctly understood the definition of CA was 30.4% in Malawi and 12.4% in Tanzania. Finally, adoption of CT

Table 5. Effect of visiting demonstration sites on adoption of soil cover in Malawi and Tanzania

	Pooled	Malawi				Tanzania	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: effect of treatment and mediator on adoption							
Visited demonstration sites	0.052***	0.036***	0.031**	0.030**	0.102**	0.090**	0.025
	(0.018)	(0.014)	(0.014)	(0.014)	(0.040)	(0.041)	(0.040)
Accurate understanding of CA	0.125***	0.079***	0.074***	0.077***	0.248***	0.254***	0.251***
	(0.020)	(0.015)	(0.015)	(0.015)	(0.048)	(0.048)	(0.047)
Household size	−0.002		0.001	0.001		−0.012*	0.003
	(0.002)		(0.002)	(0.002)		(0.007)	(0.007)
Sex	0.017		0.014	0.014		0.023	0.100**
	(0.024)		(0.019)	(0.019)		(0.050)	(0.049)
Age	0.001		0.001*	0.001*		0.001	0.001
	(0.001)		(0.001)	(0.001)		(0.002)	(0.002)
Trading center (km)	0.001		0.003***	0.004***		0.001	0.003
	(0.001)		(0.001)	(0.001)		(0.002)	(0.002)
Observations	3630	2040	2033	2033	1597	1597	1597
R^2	0.024	0.025	0.040	0.043	0.026	0.034	0.094
Panel B: estimate of ACME and ADE							
Treatment effect on accurate understanding of CA	0.899***	0.954***	0.942***	0.972***	0.842***	0.785***	0.787***
	0.050	0.060	0.061	0.063	0.084	0.087	0.088
ACME	0.034	0.025	0.024	0.026	0.047	0.045	0.046
ADE	0.053	0.037	0.034	0.029	0.105	0.098	0.023
% of treatment effect mediated	39.0	39.8	41.2	46.9	31.0	31.6	66.3
Additional covariates	Yes	No	Yes	Yes	No	Yes	Yes
Location fixed effects		No	No	Yes	No	No	Yes

Standard errors in parentheses ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.
Share of treatment effect is the % of total mediated effect × 100.

and SC at the start of the project in 2009 was just about 1% (except of CT in Malawi was adopted at a rate of about 5% in 2009).

Mediation model results for conservation tillage adoption

Tables 2–4 show the model results for the effects of the *treatment* variables (i.e., visiting demonstrations, Table 2; field days, Table 3; and training, Table 4) and that of the *mediator* variable (i.e., correct understanding of CA) on the adoption of CT and SC. As per Table 2, visits to demonstration sites and a correct understanding of CA had a strong and statistically significant influence on the probability of adopting CT. In Table 2, the effect of demonstrations on the correct understanding of CA was also highly significant at the 1% level. The shares of ATE-mediated effects were 32.5% (model 1), 36.7% (model 2) and 29.9% (model 3). This suggests that conditional on being exposed to the various extension approaches, the correct understanding of CA was closely linked to the adoption of CT and corresponded with the 30% reporting of correct understanding in the sample, as shown in Table 1. The ATE for the demonstration treatment was 43, 39 and 39% for models 1, 2 and 3, respectively.

In Table 3, the results are reported for the effects of field days in determining adoption and predicting the correct understanding of CA. The effects mirror those in Table 2. The share of treatment-mediated effects was also in the 31.5–34.4% range. The ATE constituted 38–42% of the observed effects. Table 4 shows that the shares of mediated effects were 25% (model 1), 28.5% (model 2) and 23.2% (model 3). The ATE accounted for approximately 50% of the observed effects. This was the largest effect, compared to the approximately 40% average for the models for field days and demonstrations.

Mediation model results for soil cover adoption

Tables 5–7 present the results on the effect of the *treatment* variables (i.e., visiting demonstrations, Table 5; field days, Table 6; and training, Table 7) and that of the *mediator* variable (i.e., correct understanding of CA) on the adoption of SC (mulching). The results are generally consistent with the previous results reported for CT. The treatment variables are all statistically significant (at the 1% level). The effects of the treatment variables on the understanding of CA are also highly significant (at the 1% level in all cases). As shown in Table 5, the effects of ATE ranged

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Table 6. Effect of attending field days on adoption of soil cover in Malawi and Tanzania

	Pooled	Malawi			Tanzania		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: effect of treatment and mediator on adoption							
Attended field days on CA	0.043**	0.039***	0.039***	0.039***	0.076*	0.077*	0.019
	(0.019)	(0.014)	(0.014)	(0.014)	(0.043)	(0.043)	(0.042)
Accurate understanding of CA	0.130***	0.079***	0.072***	0.074***	0.265***	0.267***	0.255***
	(0.020)	(0.015)	(0.015)	(0.015)	(0.047)	(0.047)	(0.046)
Household size	−0.002		0.001	0.001		−0.013*	0.002
	(0.002)		(0.002)	(0.002)		(0.007)	(0.007)
Sex	0.019		0.015	0.015		0.030	0.101**
	(0.024)		(0.019)	(0.019)		(0.050)	(0.049)
Age	0.001		0.001*	0.001**		0.001	0.001
	(0.001)		(0.001)	(0.001)		(0.002)	(0.001)
Trading center (km)	0.001		0.004***	0.004***		0.001	0.003
	(0.001)		(0.001)	(0.001)		(0.002)	(0.002)
Observations	3627	2037	2030	2030	1597	1597	1597
R^2	0.024	0.026	0.042	0.044	0.024	0.033	0.094
Panel B: estimate of ACME and ADE							
Treatment effect on accurate understanding of CA	0.816***	0.927***	0.921***	0.909***	0.607***	0.533***	0.523***
	0.050	0.060	0.060	0.061	0.090	0.093	0.094
ACME	0.033	0.025	0.023	0.025	0.037	0.032	0.030
ADE	0.044	0.040	0.042	0.038	0.079	0.086	0.017
% of treatment effect mediated	42.8	38.3	36.0	39.1	31.6	26.9	63.1
Additional covariates	Yes	No	Yes	Yes	No	Yes	Yes
Location fixed effects		No	No	Yes	No	No	Yes

Standard errors in parentheses ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

from 5.5% (column 4, Malawi) to 15.2% (column 5, Tanzania). The share of treatment-mediated effects was between 31.6% (model 6, Tanzania) and 46.9% (model 4, Malawi). In the field days model (Table 6), the ATE accounted for 4.7–11.2% of the total estimated effects. The share of ATEs accounted for by the mediation effect was 31.6–63.1% (column 7, Tanzania). In Table 7 (reporting the effects of training), the ATE ranged from 6.9 to 25.4%. The share of ATEs accounted for by mediation ranged from 26.9 to 38.6%.

Sensitivity results

In Figures 2, the ρ at which ACME is zero is approximately 0.1 in all three models. The estimated ACMEs were also generally similar in all three cases (demonstrations, field days and training), at 0.012 (demonstrations and field days) and 0.011 (training). Visual inspection of Figure 2 shows that the ACME at which ρ = 0 (the condition for ignorability to be satisfied) is quite close to the estimated ACMEs. Note that the sensitivity analysis here aims to detect the stability of ACME. In the manner of Imai *et al.* (2010), the question is 'how large should ρ be for the mediation effect to be zero'? Thus, to conclude that the true ACME is not significantly different from zero, the unobserved confounder positively affects *both* accurate understanding *and* adoption of CA in the same direction and the correlation between the two error terms (in the mediator and outcome models) must be greater than 0.1. Similar results are found in Figure 3 (for the adoption outcome for SC), where we find that the ρ at which the estimated ACME is zero is approximately 0.2 (0.15 in the pooled sample). On the other hand, the estimated ACME is between 0.026 (demonstration sites in Malawi) and 0.064 (training in Tanzania). The presence of any unobserved confounder would have to be such that the ρ would need to be at least 0.15 for ACME to be zero.

The adoption results presented earlier showed that exposure to demonstrations, field days and training significantly predicted whether the adopter had an accurate understanding of CA. The sensitivity results suggest that while the extension methods used here were important in positively affecting a better understanding of CA, the former affects adoption via improved know-how. The sensitivity results suggest that the mediation effects are sensitive to unobserved confounders. The relatively steep slopes of the graphs in Figures 2 and 3 suggest that although the ACME accounted for approximately 23–63% of the ATE (as per the results already presented) and although the assumption of the potential ignorability appears defensible, the ACME estimates are not insensitive to the effects of unobserved

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Table 7. Effect of training on adoption of soil cover in Malawi and Tanzania

	Pooled		Malawi			Tanzania	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: effect of treatment and mediator on adoption							
Attended training on CA	0.074***	0.047***	0.044***	0.043***	0.181***	0.174***	0.170***
	(0.020)	(0.014)	(0.014)	(0.014)	(0.052)	(0.053)	(0.052)
Accurate understanding of CA	0.121***	0.078***	0.073***	0.075***	0.223***	0.229***	0.208***
	(0.020)	(0.014)	(0.014)	(0.015)	(0.049)	(0.049)	(0.048)
Household size	−0.002		0.001	0.001		−0.012*	0.003
	(0.002)		(0.002)	(0.002)		(0.007)	(0.007)
Sex	0.021		0.017	0.016		0.026	0.107**
	(0.024)		(0.019)	(0.019)		(0.049)	(0.049)
Age	0.001		0.001*	0.001*		0.000	0.001
	(0.001)		(0.001)	(0.001)		(0.002)	(0.002)
Trading center (km)	0.001		0.004***	0.004***		0.001	0.003*
	(0.001)		(0.001)	(0.001)		(0.002)	(0.002)
Observations	3626	2036	2029	2029	1597	1597	1597
R^2	0.026	0.029	0.046	0.047	0.030	0.037	0.100
Panel B: estimate of ACME and ADE							
Treatment effect on accurate understanding of CA	0.998***	0.941***	0.951***	0.985***	1.180***	1.111***	1.129***
	0.053	0.060	0.061	0.063	0.100	0.104	0.105
ACME	0.038	0.025	0.025	0.027	0.069	0.068	0.064
ADE	0.075	0.048	0.047	0.042	0.185	0.185	0.168
% of treatment effect mediated	34.0	34.7	34.4	38.6	27.2	26.9	27.7
Additional covariates	Yes	No	Yes	Yes	No	Yes	Yes
Location fixed effects		No	No	Yes	No	No	Yes

Standard errors in parentheses ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

confounders. In the next section, we discuss the robustness of these results with respect to these unobserved outcome modifiers.

Checking the robustness of the mediation results

Since the sample of farmers adopting CT and SC is not necessarily random, we use PSM to assess the severity of selection bias in our data. The PSM procedure is an attempt to balance the distribution of observed covariates between adopters and nonadopters based on their propensity score, corresponding to the conditional probability of receiving treatment given the observable pretreatment characteristics (Colin and Trivedi, 2005). The pretreatment characteristics used for matching the treated and untreated households were district of residence, sex, membership in farmers' associations before the intervention and the self-reported qualitative description of the slope of the soil as well as the soil depth as each plot owner perceived the two variables in their farming experience.

In the PSM regressions, households that visited demonstration sites, attended field days or participated in CA training are regarded as having been 'treated', while households that did not participate in any of these activities are considered 'untreated'. Treatment is represented by a value of 1 for households that took part in any of the interventions and 0 otherwise. Households that are treated are matched with households that are untreated based on their propensity score (a single number ranging from 0 to 1 that summarizes all of the observed characteristics that influence the likelihood of being treated). The propensity score enables the matching of individuals in the control and treatment groups with the same likelihood of receiving treatment. Thus, a pair of households (one in the treatment group and one in the control group) that share a similar propensity score are seen as equals even though they may differ in the specific values of the covariates. Holmes, (2013), Figure 4 below presents an example of the propensity scores and covariate balance before and after matching for visiting the demonstration of CT in the case of Malawi, and Figure 5 shows the same for the effect of visiting demonstrations of the adoption of SC in Tanzania.

Tables 8 and 9 show the average treatment effect (ATE) for the effect of various treatments on the adoption of CT and SC, respectively. Comparing the results of the causal effect of our main specification with the results from the propensity score, the data in Tables 8 and 9 show that our main results are

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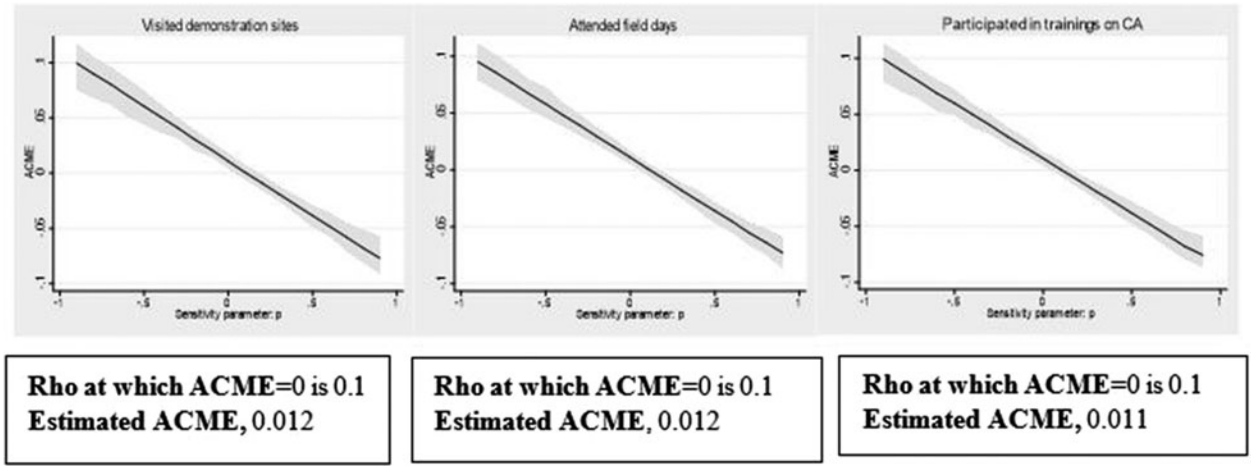

Figure 2. Sensitivity analysis of the effect of treatment variables on adoption of conservation tillage.

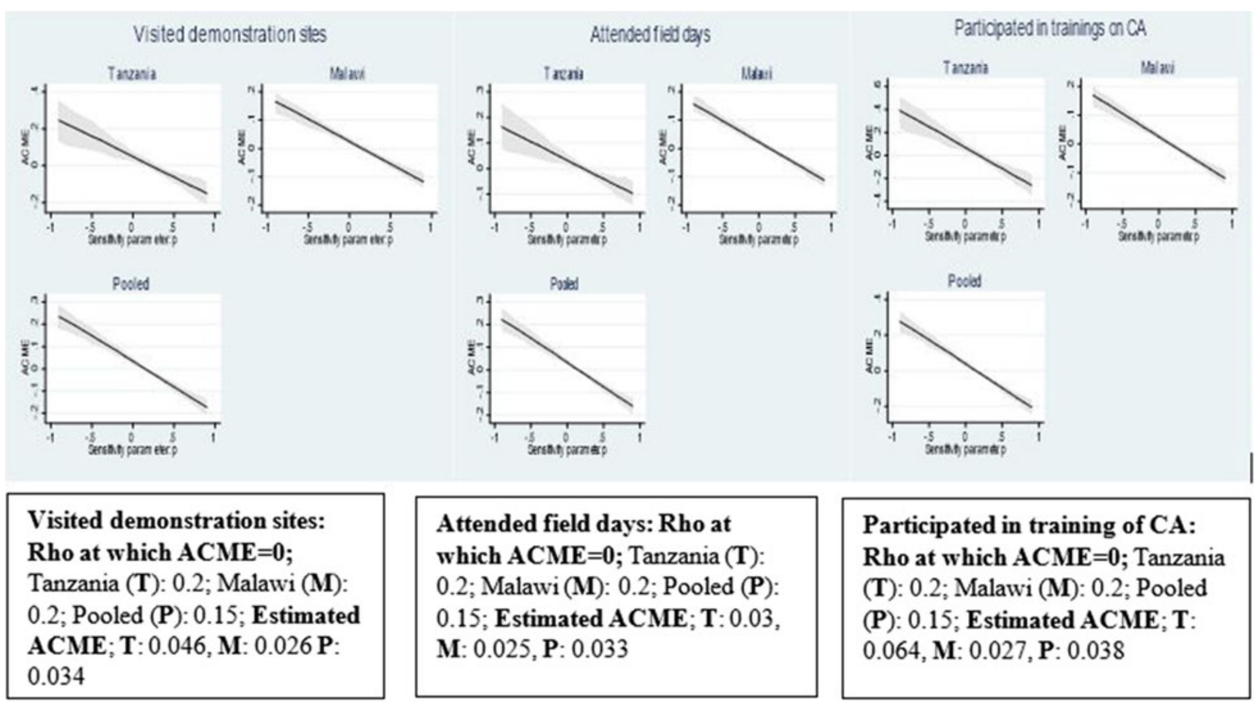

Figure 3. Effect of visiting demonstration sites, attending field days and training on adoption of soil cover.

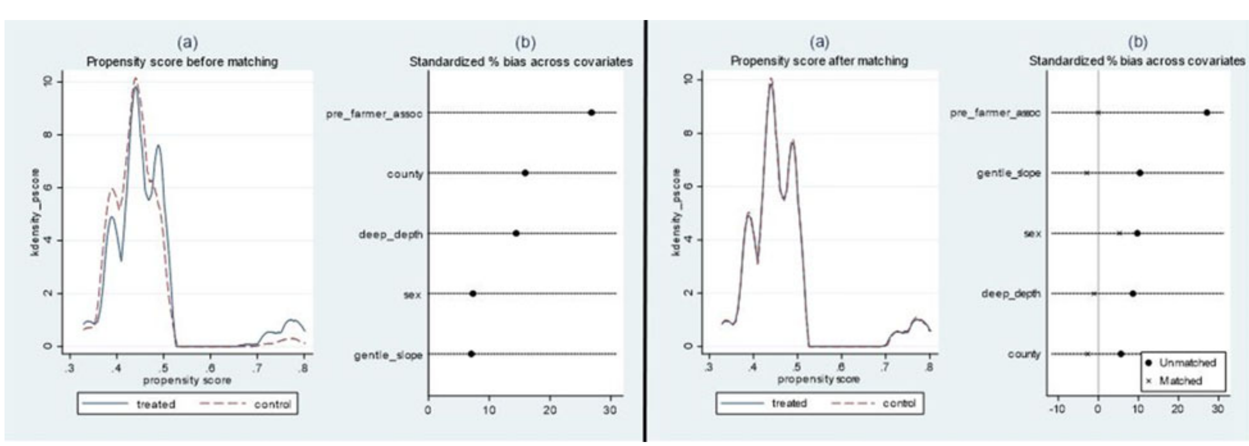

Figure 4. Propensity scores and covariate balance before and after matching in Malawi (effect of demonstrations on adoption of conservation tillage).

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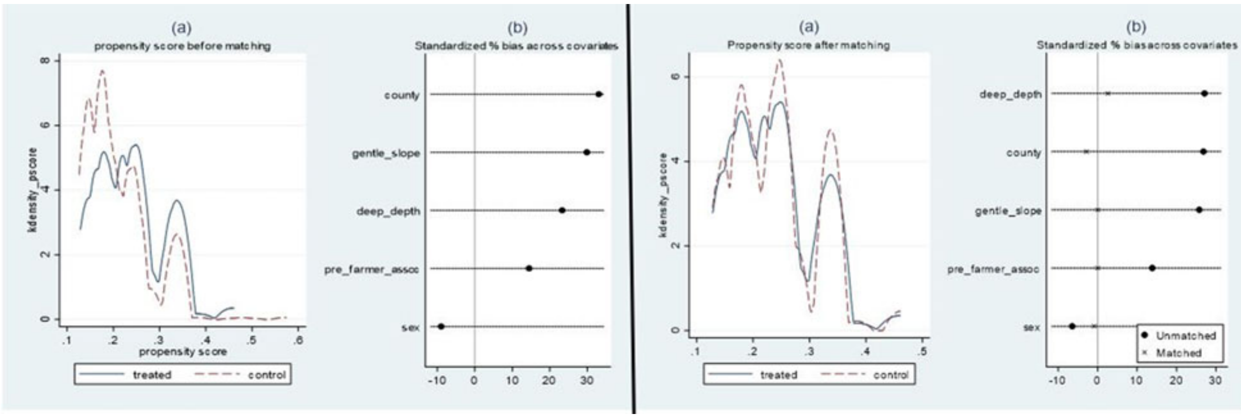

Figure 5. Propensity scores and covariate balance before and after matching in Tanzania (effect of demonstrations on adoption of soil cover).

Table 8. Comparing treatment effects from regression and PSM for conservation tillage in Malawi

	Conservation tillage		
Dependent variable	*N*	ATT (PSM)	ATT (original)
Demos	1638	0.038***	0.026***
		(0.01)	(0.004)
Field visits	1635	0.041***	0.010***
		(0.01)	(0.003)
Training	1634	0.049	0.010***
		(0.01)	(0.003)

conservative (the results obtained from our main specifications are probably in the lower bounds and likely not overestimated).

Conclusions and implications for policy

To reduce agriculture's carbon, land and water footprint, the diffusion of conservation farming methods is one critical proposition. Yet the process of translating available information on new sustainable methods into farmers' practices is often a black box in many studies. This understanding is critical to inform strategies for scaling these complex, knowledge-intensive, but necessary practices for improving agriculture's resource and climate balance sheet. By implementing a series of mediation analysis using data from 700 households in Malawi and 930 households in Tanzania, this study examines how an improved understanding of CA principles is an important mediator in the pathway from extension contact to the adoption of two of the CA practices examined. For the adoption of CT, the share of the mediated treatment effect was in the 31.5–34.4% range, while it was 31.6–46.9% for the adoption of SC (mulching).

The success of extension institutions can be measured by how much they enable the improvement of farmers' skills, allowing farmers to take charge of the recommendations and adapt them to their circumstances. This is crucial because no two farmers are identical in terms of their socio-economic characteristics, market access and the natural resources at their disposal. The extent of the presence (or absence) of these factors can amplify or dampen farmers' potential for implementing CA. Therefore, developing farmers' capacity to perform autonomous experiments and learn from them is crucial. The results presented in this paper shed light on the role of extension and its connection with improving farmers' know-how. The results show that access to various extension activities (demonstrations, field days and training) is a strong predictor of the adoption of CA practices. As we have shown from the mediation effects, the adoption effect of the extension activities was substantially mediated by the accurate understanding of CA, made possible through multifaceted contacts with extension and researchers. However, and perhaps

Table 9. Comparing treatment effects from regression and PSM for soil cover in Malawi and Tanzania

	Soil cover					
	Malawi			Tanzania		
Dependent variable	*N*	ATT (PSM)	ATT (original)	*N*	ATT (PSM)	ATT (original)
Demos	1638	0.047***	0.030**	1526	0.066	0.025
		(0.016)	(0.014)		(0.049)	(0.040)
Field visits	1635	0.075***	0.039***	1525	0.041	0.019
		(0.016)	(0.014)		(0.047)	(0.042)
Training	1634	0.062***	0.043***	1522	0.211***	0.170***
		(0.015)	(0.014)		(0.071)	(0.052)

suggesting the role of other factors that impinge on the adoption of CA, the sensitivity tests indicated that these other factors possibly muted the mediating influence. This lends weight to the notion that although an accurate understanding of CA is a critical mediator of adoption, other enabling factors must be concomitantly present to achieve maximum impact.

An important consideration is that CA practices are both information and knowledge intensive. Like most agronomic practices, they also need to be adapted to farmer's local conditions. This means that scaling CA-based solutions will need policy approaches and extension investments that promote farmer self-learning, know-how and capacity, as a priority and before promoting specific 'ready practices'. Part of this should be an emphasis on farmer-focused knowledge management and learning system that builds farmer technical knowhow, improves their agency and self-determination in the journey toward adoption of CA practices.

The policy implication is that private learning by doing must be a critical adjunct to other avenues of farmer learning. Beyond the basic promotional goals, improving farmers' technical know-how needs to be the centerpiece of holistic efforts in support of conservation farming and similar knowledge-intensive practices necessary for achieving sustainable agriculture. Even with this emphasis on individual approaches, farmers full information ecosystem includes social channels for information diffusion and social learning aspects remain an important part of this ecosystem. This is one area that requires further analysis.

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Competing interests. None.

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