14 Agricultural technology diffusion and adoption in banana- and legume-based systems of Central Africa

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Introduction

The important role of technological change and innovation in increasing agricultural productivity, economic growth and poverty reduction in sub-Saharan Africa (SSA) has been widely acknowledged and documented (World Bank 2007). The majority of the populace in SSA live in rural areas and rely on agriculture for their livelihood. Agricultural research, the main source of technological innovation, is therefore critical in the improvement of productivity with high potentials for poverty reduction and for meeting food security needs without irreversible degradation of the natural resource base. Many interventions to improve the productivity of agricultural systems have been promoted in the Great Lakes region of Africa through technological change.

The Consortium for Improving Agriculture-based Livelihoods in Central Africa (CIALCA)[1] aims at improving the livelihoods of rural households through the identification, evaluation and promotion of technological options with the objective of enhancing the productivity of banana and legume-based systems and creating an enabling environment for their adoption. The potential of the technologies developed and disseminated by the project for a marked increase in the productivity of the production systems has been demonstrated based on field trials. However, until now, not much has been known about the level of awareness of the technologies and the adoption rates. Assessing the technology adoption rates and the factors influencing them are important in priority setting, providing feedback to the research programmes, guiding policy-makers and those involved in technology transfer to have a better understanding of the modalities of the assimilation and diffusion of new technologies.

This chapter examines the adoption rates of CIALCA technologies and the factors influencing their uptake from the perspective of modern evaluation theory by employing the treatment effects approach (Heckman 1996; Wooldridge 2002). The approach is essential because the commonly used estimators for adoption rates suffer from either non-exposure or selection bias. Much of the adoption literature focuses on technology-related determinants or farmers' characteristics to estimate adoption rates (Feder *et al.* 1985; Doss 2006). Such models are based on the assumption that, once introduced, the knowledge about the new technology spreads or somehow 'diffuses' within the farming communities. The non-exposure bias arises from the fact that farmers who have not been exposed to a technology cannot adopt it, even though they might have done so if they had known about it. This leads to the underestimation of the population adoption rate (Diagne and Demont 2007). Due to the non-exposure bias, the normally computed sample adoption rate (the proportion of sampled farmers who have adopted) does not consistently estimate the true population adoption rate, even with a random sample.[2] This is because farmers self-select into exposure, and researchers and extension agents tend to target progressive farmers first (Diagne 2006). Similarly, the effects of the determinants of adoption cannot be consistently estimated using simple probit, logit or Tobit adoption models that cannot control for exposure. To account for selection bias, some authors have employed a latent variable correction procedure (e.g. Dimara and Skuras 2003). However, this approach has been criticized by Diagne and Demont (2007), who argued that the parametric latent variable formulation is not efficient since the adoption outcome variable is binary, rendering the resulting estimates 'messy'.

The true population adoption rate corresponds to what is defined in modern evaluation literature as the average treatment effect (ATE). The ATE parameter measures the effect of a 'treatment' on a person randomly selected in the population (Wooldridge 2002). In our adoption context, 'treatment' corresponds to the exposure to a technology. The consistent estimation of ATE requires controlling for exposure status and the use of a set of covariates which, in the adoption context, correspond to the determinants of adoption status commonly used in probit or logit models of adoption.

Empirical framework

The analysis in this chapter follows the modern treatment effect estimation literature using a counterfactual outcome framework proposed by Diagne and Demont (2007) to control for exposure bias in the estimation of technology adoption rates. The adoption of CIALCA technologies is assumed to be a dichotomous choice, where the technology is adopted by farmers when the perceived net benefit from adoption is greater than the result of not adopting the technology. The difference between the farmers' perceived net benefit from the adoption of the CIALCA technologies and from non-adoption may be denoted as $I^{\star}$, such that $I^{\star} > 0$ indicates that the net benefit from adoption exceeds that of non-adoption. $I^{\star}$ is unobservable, but can be expressed as a function of observable elements in the latent variable model:

$$\begin{aligned} I^{\star}_i &= \beta X_i + \mu_i, \\ I_i &= 1\ [I^{\star}_i > 0] \end{aligned} \tag{1}$$

where I_i is a binary indicator variable that equals 1 for farmer i in case of adoption and 0 otherwise, β is a vector of parameters to be estimated, X_i is a vector of explanatory variables, and μ_i is an error term assumed to be normally distributed. The probability of adopting CIALCA technologies can be represented as:

$$\Pr(I_i = 1) = \Pr(I^{\star} > 0) = \Pr(\mu_i > -\beta X_i) = 1 - F(-\beta X_i) \tag{2}$$

where F is the cumulative distribution function for μ_i. Different models, such as logit or probit, normally result from the assumptions that are made on the functional form of the cumulative distribution function F (Maddala 1983). However, these models yield biased and inconsistent estimates even when based on a randomly selected sample. This is due to 'non-exposure' bias or 'selection bias'. Farmers may not adopt a technology because they were not exposed to it, but might have adopted it had they been exposed to it. Non-separation of exposure and adoption decisions leads to an underestimation of population adoption rates. Selection bias arises because technologies are not randomly assigned to farmers. This leads to farmers' self-selection into exposure.

The true population adoption rate corresponds to what is defined in the modern treatment effect literature as the ATE. The ATE parameter measures the effect or impact of a 'treatment' on a person randomly selected in the population. With the treatment effect framework, every farmer in the population has two potential outcomes: with and without exposure to a technology. Let I_1 be the potential adoption outcome of a farmer when exposed to the CIALCA technology and I_0 be adoption outcome when not so exposed.[3] The treatment effect for farmer i is measured by the difference $I_{i1} - I_{i0}$. Hence, the expected population adoption impact of exposure to CIALCA technology is given by the mean value $E(I_1 - I_0)$, which is, by definition, the ATE.[4] However, I_1 is observed only for farmers exposed to the CIALCA technology. It is impossible to observe both the adoption outcome and its counterfactual, making it impossible to measure $I_1 - I_0$ for any given farmer.

Since exposure to the CIALCA technology is a necessary condition for its adoption, we have $I_0 = 0$ for any farmer, whether exposed to the technology or not. Hence, the adoption impact of a farmer i is given by I_{i1} and the average adoption impact of exposure is given by $ATE = EI_1$. Unfortunately, I_1 is observed only for farmers exposed to the CIALCA technology, therefore EI_1 cannot be estimated by the sample average of a randomly drawn sample. If we let the binary variable w be an indicator for exposure to CIALCA technology, where $w = 1$ denotes exposure and $w = 0$ otherwise, the average adoption impact on the exposed sub-population is given by the conditional expected value $E(I_1 \mid w = 1)$, which is by definition the ATE on the treated (ATE1). Since we do observe I_1 for all the exposed farmers, the sample average of I_1 from the sub-sample of exposed farmers will consistently estimate ATE, provided the sample is random. The ATE can be decomposed as a weighted sum of the average treatment effect on the treated (ATE1) $E(I_1 \mid w = 0)$, the expected adoption impact in the non-exposed sub-population (ATE0):

$$ATE = EI_1 = P(w = 1)\ X\ ATE1 + (1 - P(w = 1))ATE0 \tag{3}$$

where $P(w = 1)$ is the probability of exposure.[5] From (3) the expected non-exposure bias, the expected bias from using the sample average adoption rate among the exposed and the expected adoption impact in the non-exposed sub-population, can be estimated. We can also obtain the observed adoption outcome I as a function of the potential outcomes I_1 and I_0 and the treatment status (exposure) variable w as:

$$I = wI_1 + (1 - w)I_0 = wI_1 \tag{4}$$

For consistent estimation of population adoption parameters, we identify ATE based on the conditional independence (CI) assumption involving potential outcomes (Wooldridge 2002; Imbens and Wooldridge 2009). The CI assumption postulates that a set of observed covariates determining exposure, when controlled for, renders the treatment status w independent of the potential outcomes I_1 and I_0. Based on the CI assumption, ATE parameters can be estimated either with parametric or with non-parametric regression methods. We estimate ATE, ATE1 and ATE0 with parametric procedures by specifying a model for the conditional expectation of the observed variables w, x and I (Diagne and Demont 2007):

$$E(I \mid X, w = 1) = g(X, \beta) \tag{5}$$

where g is a known function of the vector of covariates X, determining the adoption of CIALCA technologies and β is the unknown parameter vector which can be estimated by maximum likelihood procedures using observations (I, X) from the exposed sub-sample with I as the dependent variable. With the estimated parameters β, the predicted values are computed for all observations in the sample, including the non-exposed. The average of these predicted values, (X, β), is used to compute ATE for the full sample, and ATE1 and ATE0 for the exposed and non-exposed sub-samples.

Contextual background

CIALCA has been operating since 2006 in ten mandate areas in DRC, Rwanda and Burundi.[6] These areas have some of the largest population densities in Africa, with average values ranging between 238 and 514 people/km^2. CIALCA has promoted the technology options of integrated soil fertility management (ISFM) and integrated pest management (IPM) as a framework for the enhanced productivity of banana and legume system components. These technology options comprise improved germplasm, the promotion of efficient fertilizer use, optimized organic matter management and local adaptation. The production–consumption continuum has been applied to link the actors in the system value chain, from the inputs required for production to delivery to the consumers. In order to catalyse the adoption of technologies to enhance productivity, interventions have been promoted that improve the security of income and nutrition. Interventions intended for nutrition security include the promotion of foods enriched with soybean and dietary diversification. Income enhancement has been promoted by applying market linkage approaches through collective efforts among smallholder farmers.

The data

The data used in our analysis were derived from a cross-sectional household survey in 2011 covering 913 farmers in Burundi, DRC and Rwanda. The sample design followed a multi-stage procedure to select mandate area, village and households. The survey covered seven mandate areas, intentionally selected because of the intensity of CIALCA interventions. Five villages were then randomly selected in each of the mandate areas stratified into three categories. The first, also known as 'action sites', consisted of villages that hosted demonstrations of the technologies. Action sites are selected sites in each mandate area in which field activities related to technology identification, evaluation and adaptation are implemented. The second, also known as 'satellite sites', involved neighbouring villages where development partners were involved in scaling out CIALCA technologies. The third consisted of control villages which had agro-ecological conditions similar to those of the action and satellite sites but without any CIALCA interventions. They were within a 10–15 km radius of the action and satellite sites. Households were then randomly sampled, proportional to size, to yield a sample of approximately 130 households/mandate area.

Descriptive statistics of adoption status for several variables are presented in Table 14.1. The full sample consisted of 913 households, of which 32 per cent were adopters of CIALCA technologies. Adoption was defined as the use of any of the ISFM and/or IPM options promoted by CIALCA during the last season. The variables in Table 14.1 were used in the estimation of the econometric models.

Table 14.1 Descriptive statistics: mean of variables by status of adoption

Variables	*Full sample* $n = 913$	*Adopters* $n = 290$	*Non-adopters* $n = 623$	*t-values*
Gender (1 = male)	0.82	0.85*	0.80	1.82
Years of agricultural experience	23.92	22.11***	24.75	–4.61
Education0 (1 = no formal education of household head)	0.25	0.17***	0.29	–3.99
Education1 (1 = primary level of household head)	0.49	0.51	0.48	0.88
Education2 (1 = secondary level of household head)	0.23	0.29***	0.19	3.37
Education3 (1 = post-secondary level of household head)	0.01	0.01	0.00	0.76
Farmers' group membership (1 = yes)	0.41	0.61***	0.31	7.99
Cultivated land area in acres	276.62	334.51	248.4	0.49
Number of plots	2.54	2.71***	2.46	2.82
Household size	5.84	6.16***	5.69	2.69
Dependency ratio (%)	41.9	42.09	41.88	0.12
Log (value of assets owned in USD)	6.73	7.29***	6.47	3.95
Off-farm income access (1 = yes)	0.24	0.24	0.23	0.12
Agricultural extension (1 = yes)	0.74	0.83***	0.69	4.61
Occupation of household head (1 = agriculture)	0.91	0.89	0.92	–1.04
Radio ownership (1 = yes)	0.62	0.68***	0.59	2.48
CIALCA training participation (1 = yes)	0.32	0.45***	0.24	5.82
Bas-Congo mandate area	0.15	0.11**	0.16	–2.12
North Kivu mandate area	0.14	0.13	0.14	–0.27
South Kivu mandate area	0.13	0.20***	0.09	4.34
Umutara mandate area	0.14	0.13	0.14	–0.48
Gitega mandate area	0.15	0.11**	0.16	–2.00
Kigali-Kibungo mandate area	0.16	0.23	0.12	4.26
Rusizi mandate area	0.15	0.09***	0.17	–3.55

Notes: ***, ** and * means that mean values for adopters are significantly different from those of non-adopters at the 1, 5 and 10 per cent level.

The difference between adopters and non-adopters of CIALCA technologies seemed to be related to institutional factors rather than to financial, natural or physical endowments. Mandate areas, specifically Kigali-Kibungo and South Kivu, had a higher proportion of adopters than the rest. This may be due to linkages with development partners working in these areas that scale out CIALCA technologies. In Kigali-Kibungo, for instance, the government of Rwanda is implementing projects that promote improved crop productivity through improved access to seeds. In South Kivu, several non-government organizations (NGOs) are working on agricultural development projects.

Results

The analysis followed two stages which were estimated simultaneously. In the first, probit models were used to analyse the determinants of CIALCA technology awareness. In the second, probit models that control for awareness exposure using the ATE framework were used to estimate unbiased adoption parameters. Table 14.2 presents the results from the probit estimation of the determinants of CIALCA technologies awareness. The log likelihood function of −192.8 and the highly significant likelihood ratio statistic show good model fitness.

The positive and significant coefficient on group membership points to the important role played by social networks in disseminating technology information. The importance in agricultural technology dissemination of social networks, such as interactions with neighbours, farmers' groups, churches and input suppliers, has been widely documented (Bandiera and Rasul 2006; Matuschke and Qaim 2009). Similarly, the positive coefficient on radio ownership shows the importance of this communication equipment in raising awareness of CIALCA technology. The probability of awareness of CIALCA technologies was 8.3 percentage points higher for farmers with a radio compared to those without, *ceteris paribus*. This is expected, since information on some of the CIALCA technologies was largely transmitted through the mass media by CIALCA or its partners.

The location-specific variables revealed a difference in the exposure of CIALCA technology over space.[7] For instance, the probability of awareness of CIALCA technologies was 40 percentage points lower for farmers in Bas-Congo and 13–33 percentage points lower in Gitega, Rusizi and Umutara compared with farmers located in the Kivus, *ceteris paribus*. The marginal effect on Kigali-Kibungo was not statistically significant. In North and South Kivu, CIALCA has used local radio programmes to inform the population on some of its technologies. This result may be a reflection of the effectiveness of radio programmes in reaching out to farmers in rural areas.

Table 14.3 presents the results of CIALCA technology adoption models with two alternative specifications: the ATE corrected model for exposure and the classical adoption probit that does not account for exposure bias. Similarities in terms of the coefficient signs, significant levels of the coefficients and

Table 14.2 Determinants of exposure to CIALCA technologies

Variables	*Marginal effects*†	*z-value*
Gender	0.031	0.84
Age of the household head	–0.000	–0.20
Farmers' group membership	0.074**	2.52
Agricultural extension	0.047	1.34
Radio ownership	0.083**	2.39
CIALCA trainings	0.132***	5.09
Log assets	0.004	0.86
Bas-Congo	–0.400**	–2.03
Umutara	–0.133*	–1.45
Gitega	–0.331***	–3.20
Kigali-Kibungo	–0.132	–1.45
Rusizi	–0.191*	–1.82
Summary statistics		
Pseudo R-squared	0.161	
LR Chi-square	73.98***	
Number of observations	519	
Log likelihood function	–192.786	

Notes: ***, ** and * denote statistical significance at the 1, 5, and 10 per cent level. † Marginal effects evaluated at sample means.

marginal effects are observed for the two models. Access to agricultural extension and membership in farmers' groups positively influenced the likelihood of adoption of CIALCA technologies. This implies that the two pathways were the main avenues for access to CIALCA technologies.

Although some of the coefficient signs and levels of significance were similar in the two models, the magnitudes of the coefficients and marginal effects tended to be rather different. In the ATE treatment, the effects are smaller because the variable on exposure has already been accounted for. For example, group membership increases the probability of exposure to the technologies, and those among the exposed in the group are more likely to adopt. The coefficient on off-farm income was negative and significant in the ATE-corrected model though insignificant in the classical model. This implies that access to off-farm income had a negative effect on adoption. The probability of adopting CIALCA technologies was 14 percentage points lower among farmers with access to off-farm income compared with those without it. While off-farm income may provide the financial liquidity needed for technology adoption, it may also be an indication of a specialization away from agriculture which could result in a lower level of interest in new technologies.

Farm size and the ownership of productive assets did not influence adoption significantly, implying scale-neutrality of the technologies. This has also been

Table 14.3 Determinants of CIALCA technologies adoption

Variables	*ATE corrected model for exposure*			*Classical adoption model*		
	Estimated coefficients	*S.E.*	*Marginal effects*	*Estimated coefficients*	*S.E.*	*Marginal effects*
Gender	0.041	0.199	0.025	0.144	0.183	0.053
Age	0.001	0.035	0.004	0.010	0.033	0.004
Age-squared	−0.000	0.252	0.000	−0.000	0.237	−0.000
Education0	−0.204	0.176	−0.079	−0.353	0.164	−0.126
Education1	0.124	0.242	0.049	0.099	0.235	0.037
Education2	0.537	0.164	0.212	0.562	0.152	0.218
Occupation of household head	−0.339	0.531	−0.135	−0.371	0.499	−0.144
Household size	0.027	0.289	0.011	0.029	0.277	0.011
Dependency ratio	−0.001	0.144	−0.000	−0.002	0.137	−0.000
Farmers' group membership	0.376***	0.335	0.149***	0.523***	0.321	0.196***
Agricultural extension	0.359**	0.308	0.081	0.378**	0.365	0.135***
Radio	0.081	0.275	0.032	0.127	0.260	0.047
Log of asset value	0.032	0.250	0.013	0.037	0.233	0.014
Cultivated land area	0.001	0.057	0.000	0.000	0.053	0.000
No. of plots	0.001	0.026	0.000	0.015	0.025	0.005
Off-farm income	−0.361*	0.168	−0.142**	−0.254*	0.235	−0.093*
Bas-Congo	−0.458	0.000	−0.145	−0.477	0.000	0.094
Gitega	−0.563*	0.033	−0.027	−0.792**	0.031	−0.036
Kigali-Kibungo	0.043	0.003	0.265	0.084	0.003	0.238
Umutara	−0.396	0.364	0.066	−0.499*	0.343	0.077
Rusizi	0.593*	0.292	−0.225**	−0.720**	0.271	−0.234***
Constant	−1.576	0.965	–	−1.740**	0.921	–
Summary statistics						
Pseudo *R*-squared	0.135			0.167		
LR Chi-square	73.808***			104.465***		
N	398			472		
Log likelihood function	−237.15			−261.52		

Notes: ***, ** and * denote statistical significance at the 1, 5, and 10 per cent level. Marginal effects evaluated at sample means.

found in many other studies related to the adoption of agricultural technologies, such as Edmeades and Smale (2006) and Kabunga *et al.* (2011). Besides, most of the farmers in the region were small-scale farmers with small land holdings.

Some of the location-specific variables had significant coefficients. Gitega, Umutara and Rusizi mandate areas had negative and statistically significant coefficients in the model, implying that the likelihood of adoption was lower in these areas than in the Kivu area. The marginal effects were, however, significant only for the Rusizi mandate area. The coefficient on Kigali-Kibungo was not statistically significant compared to the Kivus. In the Kivu area, membership in farmers' groups was relatively high compared to other mandate areas and the high likelihood of adoption of CIALCA technologies from the model results may have been due to information exchanges among farmers.

Table 14.4 presents the predicted adoption rates with and without ATE correction for exposure bias. The observed adoption rate for the entire sample (Na/N) was 37 per cent. The joint exposure and adoption rate (JEA) was 38 per cent in the ATE-corrected model. The similarity between the observed adoption rate and the JEA is expected, as indicated by Diagne and Demont (2007), although they are not good indicators of the potential population adoption rate due to non-exposure bias.[8]

The predicted adoption rate for the full population (ATE) corrected for awareness exposure is 46 per cent. Thus, if all farmers were aware of the CIALCA technologies, the adoption rate would be 8 per cent higher than that

Table 14.4 Predicted adoption rates

Variables	*Estimate*	*S.E.*	*z-value*
ATE-corrected population estimates			
Predicted adoption rate in the full population (ATE)	0.456***	0.022	20.94
Predicted adoption rate in exposed sub-population (ATE1)	0.489***	0.021	22.23
Predicted adoption rate in unexposed sub-population (ATE0)	0.336***	0.028	12.20
Joint exposure and adoption rate (JEA)	0.378***	0.017	22.23
Population adoption gap (PAG)	−0.078***	0.006	−12.48
Population selection bias (PSB)	0.033***	0.004	7.17
Observed sample estimates			
Exposure rate (Ne/N)	0.773***	0.018	41.96
Adoption rate (Na/N)	0.374***	0.021	17.58
Adoption rate among exposed sub-sample (Na/Ne)	0.483***	0.027	17.58

Note: ***, ** and * denote statistical significance at the 1, 5 and 10 per cent level. Robust standard errors are reported.

observed in the sample, i.e. the population adoption gap, JEA minus ATE, is 8 per cent. The predicted adoption rate among the presently exposed sub-population (ATE1) was estimated at 49 per cent, being slightly higher than that of the full population (ATE), indicating a positive population selection bias (PSB) in the magnitude of 3.3 per cent. This is not surprising, as most innovative farmers self-select into exposure. The predicted adoption rate in the non-exposed sub-population was calculated as the average treatment effect on the untreated (ATE0), and was 33 per cent. This is the adoption rate among the non-exposed population after becoming exposed to the technologies.

Adoption constraints

The exposure rate to CIALCA technologies was relatively high, with 77 per cent of the sampled households being aware of them. However, awareness did not necessarily translate into adoption. Figure 14.1 shows the reasons for non-adoption by those who were aware of the technologies.

Poor access to technologies was one of the major reasons for non-adoption. For instance, the supply of the improved germplasm could not meet the demand. The technology package for IPM was not adopted by farmers in areas where banana pests and diseases were not perceived as a major challenge. However, farmers had no access to some of the components of IPM, such as those for sterilizing the farm equipment.

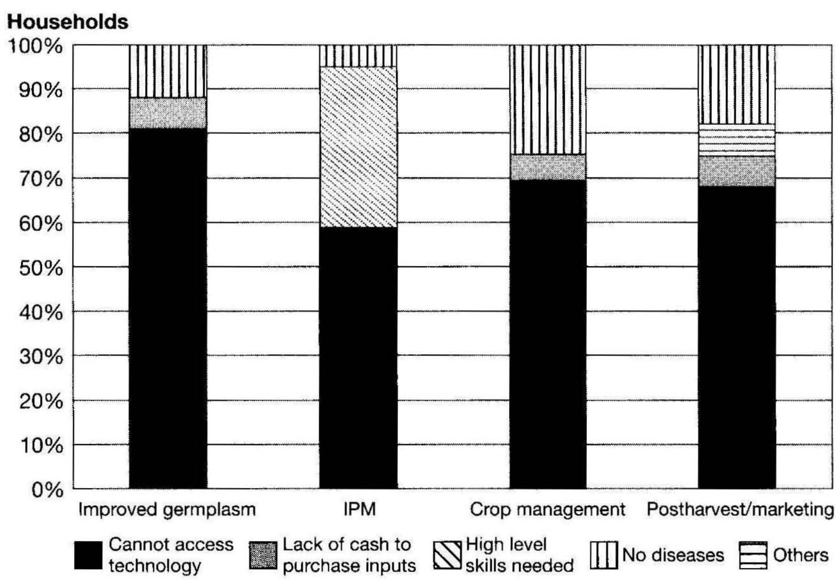

Figure 14.1 Constraints to adoption.

Summary and conclusion

We have analysed the adoption rates and factors influencing the adoption of CIALCA technologies in banana- and legume-based farming systems of Central Africa using data from a survey of farming households. The ATE framework has been applied to control for selection bias that may arise from a lack of awareness or a partial exposure to the technologies. At the population level, the results show that with exposure, the adoption rates could be slightly higher at 46 per cent. Generally, exposure rates to CIALCA technologies are high, with about 77 per cent of the sampled households being exposed. However, the corresponding adoption rates of 38 per cent are relatively low. The major constraint to adoption still remains poor access to the technologies. The marginal effects from the model estimations show the important role of farmers' groups in exposure to and adoption of technologies. Extension services from governments and NGOs are significant in the adoption models. These are the main routes for farmers to gain access to improved technology. This implies that the implementation of sustainable technological change in smallholder agriculture at scale needs to consider more efficient models of technology delivery. Such delivery models should build on existing social structures and networks at community levels to complement the traditional extension services. To reduce outreach costs, greater targeting of communication tools, such as radios, needs to be emphasized to increase exposure. For agricultural intensification to be sustainable, through efforts such as ISFM and IPM, the farmers' access to these technologies needs to be improved as some of the necessary inputs required may be unavailable.

Notes

1 CIALCA is a consortium of the International Institute of Tropical Agriculture (IITA), Bioversity International and the International Centre for Tropical Agriculture (CIAT) and their national research and development partners, supported by the Belgian Directorate General for Development Cooperation.
2 The standard sample adoption rate confounds information on diffusion and adoption of a technology, as it estimates the proportion of households who are exposed to the technology and have adopted it. By confounding the two types of information, the sample adoption rate provides unclear policy or research messages.
3 The adoption outcome in this case is the adoption status, a dichotomous 0–1 variable.
4 I_1 and I_0 are considered random variables, representing the potential outcome of any farmer randomly selected from the underlying population of farmers.
5 Used strictly to mean awareness of the existence of the new technology and does not necessarily imply any learning of its characteristics.
6 Mandate areas are defined as areas with similar agro-ecological conditions and poverty profiles that have nonetheless relatively good access to large urban markets. Mandate areas are different in surface area between the two target countries. The number of people living in each mandate area can vary between 300,000 and 1,200,000.
7 North and South Kivu have been left out of the model and are used as the comparison base.
8 The observed sample adoption rate and the joint exposure and adoption rate are similar since a random sample should yield consistent estimates of the population counterpart.

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