The effects of adopting sustainable farming practices on smallholders

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Abstract: Environmental protection is assessed from the degree of the adoption of anti-erosive measures for the protection of natural capital on land. In examining a pronounced degradation of agricultural land, this article analyses the profitability of sustainable agricultural practices for smallholders of millet and sorghum. The analysis is based on a sample of 194 observations for which the actors show different degrees of sustainable agricultural practice adoption. Multinomial logit model and propensity score matching results show that the intensive adoption of water and soil conservation is most beneficial to farmers in the studied region. The results show that in terms of economic policies for the protection of land capital, it is more advantageous to promote the intensive adoption of sustainable agricultural practices. Such a result is proven both economically and environmentally significant.

Keywords: sustainable practices; profit; adoption; smallholders; soil and water conservation.

JEL codes: Q01, Q15, N57.

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1 Introduction

Conventional agriculture has been known for many decades to involve heavy water consumption, soil erosion and organic losses leading to low yields. Appropriate responses to these issues started to emerge many years ago. Conservation tillage (Gould et al., 1989; Marra and Ssali, 1990; Rahm and Huffman, 1984), traditional soil erosion control (Carlson et al., 1994; Okoye, 1998), organic input (Clay et al., 1998), mulch tillage (Uri, 1997) and water and soil conservation methods (Shiferaw and Holden, 1998) are conservation agriculture (CA) technologies widely used by farmers internationally. However, all of these methods have been packaged under the labels of CA (Knowler and Bradshaw, 2007) and sustainable agriculture practices (Rodriguez et al., 2009).

Water and soil conservation methods apply biological and physical approaches. As biological approaches, we can use cover crops, intercropping, fallowing, alley cropping, no till methods, manuring, and legume rotation. Physical techniques include ridging, shelterbelt adoption, terracing, bunding, agroforestry, woodlot construction, taungya cultivation, stone line use, strip cropping, vetiver use, animal traction, and drainage ditch construction (Knowler and Bradshaw, 2007).

Sustainable agricultural practices are widely promoted, and their results are increasingly discussed as efficient technologies for the achievement of sustainable agriculture goals (Mrabet et al., 2012; Piñeiro et al., 2020; Rodriguez et al., 2009). Such sustainable technologies are perceived to benefit of improve yields, reduce erosion, increase soil organic matter content and decrease labour costs.

Piñeiro et al. (2020) show that for small-scale farmers who expect results in the short-term, gains may be delayed, which may lead them to abandon such practices. Bizoza and De Graaff (2012) question whether a consistent match occurs between adoption and financial profitability. For the latter, the use of sustainable agricultural practices should be accompanied by financial gains. For Giller et al. (2011), the adoption of sustainable agricultural practices has a questionable impact on expected results, namely in terms of increased yields, reduced labour, improved soil fertility and reduced erosion. In the event that these effects are proven, this should help improve the profits of smallholders.

In the case of small semiarid farms, is it beneficial for farmers to use these practices? With a focus on smallholder farming, this paper aims to assess the treatment effects of farmers using different combinations of water and soil conservation methods.

The main objective is to evaluate adoption effects on profits through two approaches: a multinomial logit model and propensity score matching. By these means, we obtain the associated determinants.

In the next sections, we successively present an empirical discussion, the methodology used and the study area examined. Section 3 analyses the obtained results before concluding the paper.

2 Empirical discussion

To improve the yields and economic profitability of conventional rice and wheat cropping systems, Choudhary et al. (2018) argue that sustainable agricultural practices are necessary. Over a three-year study, the authors combine sustainable tillage mechanisms and tailings and water resource management to improve economic yields and profitability. The authors show that the combination of maize and wheat production with the use of sustainable practices saves irrigation water and improves yields by 12% and economic profitability by 34% relative to the cultivation of conventional crops such as rice and wheat.

Despite these results, Choudhary et al. (2018) note low adoption rates of sustainable agricultural practices by farmers in the studied region due in part to government preferences for rice cultivation and due to the limited financial resources at their disposal.

Bizoza and De Graaff (2012) show that the use of water and soil conservation tools, such as bench terraces, helps decrease soil erosion and improve fertility without guaranteeing a return on investment. The authors show that despite considerable efforts made to promote such technologies, many farmers have not yet introduced them into their farming systems due to the major investments involved. Bizoza and De Graaff (2012), using an advantage-cost approach, conclude that such techniques are not financially viable under operating conditions given the high costs of labour and fertiliser. However, when used intensively, such methods become financially profitable.

Reduced fuel and labour costs, soil conservation and moisture retention are the most commonly stated reasons for the adoption of CA principles by farmers in Australia (Kirkegaard et al., 2014). However, the implementation of these sustainable practices has had mixed results. Kirkegaard et al. (2014) show that even in a relatively high-adopting country such as Australia, we should expect a similarly imperfect adoption of CA in the diverse smallholder systems of Sub-Saharan Africa and South Asia, which have the same biophysical characteristics. At the farm and village levels, trade-offs in the allocation of resources become important in determining how CA may fit into a given farming system (Giller et al., 2011).

There is a need to contextualise the implementation of sustainable agricultural practices, and the findings in this area are mixed. This sentiment is shared by Knowler and Bradshaw (2007), who conclude on the basis of a global study that there is a lack of universal variables that explain the adoption of CA and that effort to promote sustainable agricultural practices need to be tailored to local conditions.

Such studies underline the economic, institutional or social factors influencing the adoption of CA. Economically, sometimes the associated benefits cannot motivate farmers because of the cost of fertilisers or credit access. Profits are also linked to the quality of technology implementation (Bolliger et al., 2006) and to off-farm work opportunities, which can be more competitive. Social and institutional factors at play include limited access to inputs, delicate management of land tenure and strong competition from the off-farm labour market (Baudron et al., 2007; Kaumbutho and Kienzle, 2007; Shetto and Owenya, 2007).

3 Methodology

Available water and soil conservation techniques are varied. In this case study, we examine the use of manure, fertilisers, bowl water, stony ropes and drainage ditches. Farmers use these technical methods alone and in combination according to their needs.

To generalise our results, a methodological approach is chosen based on the potential differences in the effects of sustainable practices according to the adoption criteria used by each category of farmer. For this reason, a distinction is made between farmers who do not adopt any sustainable practices, those who adopt them moderately and those who adopt them intensively. The first step in extrapolating the results involves comparing the average effects of those who adopt sustainable practices to the average effects of those who do not. This first level of evaluation provides an overview of effects that does not take into account disparities in the adoption of these practices. The continuation of the methodological approach allows for a deeper understanding of the results by distinguishing between degrees of adoption. This analysis takes into account increases in costs that occur with the intensity of adoption and the gains that may or may not be elastic depending on the intensity of adoption. At this level, we obtain an evaluation that differentiates effects by degree of adoption.

Thus, the methodological approach adopted is based on a sequential evaluation of the expected effects of agricultural practices. Thus, after obtaining our data, our use of matching allows us to initially compare the performance of individuals who have used sustainable agricultural practices to the performance of those who have not. At this stage, no distinction is made between degrees of intensity, and only two groups are considered: users and non-users. As a second step, the use of the multinomial approach allows us to consider the intensity of sustainable agricultural practice adoption in the analysis (Hassan and Nhemachena, 2008; Hausman and Wise, 1978; Wu and Babcock, 1998). This approach allows us to evaluate the results for non-users, moderate users and intensive users, reflecting a further development of the assessment of effects of agricultural practices for smallholders. To account for endogeneity effects, we justify our estimations using the generalised method of moments.

3.1 Data

This study was conducted as part of a specific program intended to support farmers in rural areas under the framework of a program of the Environment and Agricultural Research Institute[1] in Burkina Faso. Thus, for empirical purposes, stratified random sampling was carried out. This program randomly selected a sample of rural farmer volunteers. Two stratification criteria were used to select the sample.

The stratification criteria selected include land ownership and agricultural activity as main activities. Land ownership is a major determinant of the adoption of sustainable practices (Akram et al., 2019; Nkomoki et al., 2018; Salaisook et al., 2020). Indeed, given the investments to be made for the adoption of sustainable practices, farmers are willing to make them when they own the land. Moreover, when agricultural activity is secondary, the adoption sustainable agricultural practices will be negatively affected, and hence the criterion of choosing agricultural activity as the main activity is adopted.

For population size *N*, the approach of Cochran (1977) allows us to determine the optimal sample size for a finite population at the 95% threshold.

$$n = \frac{z^2 p(1-p)/e^2}{1 + \frac{\left[\left(z^2 p(1-p)/e^2\right) - 1\right]}{N}}$$

where n is the sample size, z is the selected critical value of the desired confidence level, p is the estimated proportion of an attribute present in the population, and e is the desired level of precision.

Based on an estimated sample of 500 farmers and a margin of error of 5%, the sample size is determined to be 218 farmers. The processing of the observations yields a stratified random sample of 194 farmers with millet and sorghum designated as the crops grown in the program.

Propensity score matching with a small sample does not alter the estimator's quality by taking into account the propensity score as weights in small samples (Holmes and Olsen, 2010; Pirracchio et al., 2012). The sample was created by selecting farmers according to their land tenure and socioeconomic conditions. All of the studied individuals are landowners, and agriculture is their main activity. Among the farmer sample, a random process is used to obtain factual and counterfactual groups.

In addition, depending on the comparison conducted, a control group adopting similar crops and techniques was used. The investigation shows that in the study sample, most farmers apply the techniques, and sorghum is considered the most convenient crop.

Table 1 shows that intensive adoption is more often used by farmers than low adoption.

Table 1 Distribution by intensity of adoption

	Millet	*Sorghum*
No adoption ($D = 0$)	26	46
Low adoption ($D = 1$)	12	22
Strong adoption ($D = 2$)	34	54
Total	72	122

Source: National Institute of Environment and Agricultural Research, Burkina Faso (2015)

The data characteristics of the different variables are shown in Table 2.

Table 2 Variable statistics

Variable	*Obs.*	*Mean*	*Std. dev.*	*Min*	*Max*
adopt	194	1.082474	0.9067405	0	2
crop	194	1.628866	0.4843582	1	2
yield	194	1290.722	785.1633	100	4,200
site	194	2.123711	0.9134315	1	4
age	194	49.21649	13.06518	25	71
education	194	0.0618557	0.2415165	0	1
profit	194	201985.8	175912.9	4,015	610,174
area	194	5.036082	1.624373	2	8.5
sex	194	1.072165	0.2594303	1	2
active persons	194	4.298969	1.367005	1	7
agr_device	194	0.1134021	0.317904	0	1
off farm activity	194	2.845361	1.605303	1	6

Source: National Institute of Environment and Agricultural Research, Burkina Faso (2015)

3.2 Propensity score matching

Propensity score matching assesses the effect of technology adoption on agricultural productivity (González, 2009). Let us denote Y_1 and Y_0 as the adoption and no-adoption outcomes, respectively, according to technology applied or not applied. We define the propensity score (Rosenbaum and Rubin, 2006; Smith and Todd, 2005) as the conditional probability of adopting the technology given the observed covariate X:

$$p(X) = prob\{D = 1 \mid X\} = E\{D \mid X\}$$

where $D = 1$ if the farmer has applied the technology and the value is 0 otherwise.

Before evaluating the average treatment effect on treated (ATT), we must make assumptions about two conditions using the conditional independence assumption (Imbens, 2000), which stipulates that given the propensity score, covariate X should not be correlated with dummy variable D:

$$D \perp X \,|\, p(X)$$

The second hypothesis allows us to ensure the existence of a control unit for each treated unit.

$$Y_1, Y_0 \perp X \,|\, p(X)$$

Then, the average treatment effect on the treated is estimated by the following expression:

$$\begin{aligned}\Delta^{ATT} &= E\{Y_{1i} - Y_{0i} \,|\, D_i = 1\} \\ &= E\{E\{Y_{1i} - Y_{0i} \,|\, D_i = 1, p(X_i)\}\} \\ &= E\{E\{Y_{1i} \,|\, D_i = 1, p(X_i)\} - E\{Y_{0i} \,|\, D_i = 0, p(X_i)\} \,|\, D_i = 1\}\end{aligned}$$

To avoid selection bias, Δ^{ATT} becomes:

$$\Delta^{ATT} = \frac{1}{N_1} \sum_{i \in D=1} \left[Y_i^1 - \sum_{j \in D=0} \omega_{ij} Y_j^0 \right]$$

where N_0 (respectively N_1) is the number of observations of the control group for which $D_i = 0$ (and that of the treated group for which $D_i = 1$ and ω_{ij} is the weight of each j^{th} individual of the control group such that $\sum_{j \in D=0} \omega_{ij} = 1$.

From the results of the multinomial logit model and propensity score matching, we compare average treatment effects on benefits of the adoption of water and soil conservation techniques.

3.3 Multinomial logit approach

Many studies have used a probit or logit model to identify determinants of technology adoption by farmers. In some cases, steps are divided into two stages with a bi-probit, which is a sequential model wherein the determinants of the perception are detected before determining the adoption level (Amsalu and De Graaff, 2007). A strictly dichotomous variable is often not sufficient to examine the extent and intensity of the use of technologies (Anley et al., 2007). When the continued use of technologies must be measured, specification involves more than two stages. The sequential steps are divided into acceptance, adoption and continued use phases (De Graaff et al., 2005).

As one more feature of this research, all actors have been sensitised to and given the basic knowledge required to implement the studied practices.

The principle of technology application here involves adopting one or several of technologies at the same time, such as farmers' adoption of a package. Therefore, a multinomial logit method is used to model the alternatives chosen by farmers (Babcock et al., 1995; Hassan and Nhemachena, 2008; Nkamleu, 2007).

Let us denote u_i^* as the expected utility of farmer *i* according to the technologies used (combined or not) and Y_i is the observed variable denoting the technological package adopted by farmers. $u_{i;N}^*, u_{i;L}^*$ and $u_{i;S}^*$ denote the utility with no technology application, some technology application and intensive technology application, respectively.

We have

$$A_j = \begin{cases} 0 & \text{if } u_{i;N}^* > u_{i;L}^* \text{ and } u_{i;N}^* > u_{i;S}^* \\ 1 & \text{if } u_{i;L}^* > u_{i;N}^* \text{ and } u_{i;L}^* > u_{i;S}^* \\ 1 & \text{if } u_{i;S}^* > u_{i;N}^* \text{ and } u_{i;S}^* > u_{i;L}^* \end{cases} i = 1, \ldots, N \text{ and } j = 0, 1, 2.$$

No technology application denotes that zero practices are used; some technology application means that at most three techniques are used, and intensive technology application means that more than three techniques are used.

According to the choices made by the farmers, we define the probability of choosing the *j*-value (Greene, 2003; Maddala, 1983) as follows:

$$Prob(y_i = j) = p_j = \frac{\exp(u(x_i))}{\sum_{k=0}^{2} \exp(u(x_{i,k}))}; i = 1, \ldots, N \text{ and } j = 0, 1, 2$$

where $u(x_i)$ is the individual utility depending on x_i and x_i is the vector of the observed values of the explanatory variables (the instruments of the global function).

We assume that $u(x_{i,j}) = v(x_{i,j}) + \varepsilon_j = x_i\beta_j + \varepsilon_j$ where β_j is the coefficient vector of outcome *j*, and ε_j is the disturbance. We apply this linear utility function because we assume that the parameters β_j are different according to the technology choices made by farmers.

We have an independent logit multinomial, for which the globally concave likelihood function (Hausman and McFadden, 1984) is:

$$\log L(A, \alpha_j, \alpha_k) = \sum_{i=1}^{N} \sum_{j=1}^{2} A_{i,j} x_i \alpha_j - \sum_{i=1}^{N} \log\left[1 + \sum_{k=1}^{2} \exp(x_i \alpha_k)\right]$$

This model is limited by the independence of an irrelevant alternative (Hausman and McFadden, 1984; Tse, 1987).

Ratio $\frac{p_j}{p_k} = \frac{Prob(A_i = j)}{Prob(A_i = k)} = \frac{\exp(x_i \alpha_j)}{\exp(x_i \alpha_k)} = \exp[z_i(\alpha_j - \alpha_k)]$ is supposed to be independent of other alternatives. The Hausman and McFadden (1984) test addresses this problem.

The α coefficients are irrelevant to estimate as marginal effects (Greene, 2003). The marginal effects that assess the probability of a farmer changing his or her behaviour (Greene, 2003; Wooldridge, 2010) are derived by the following:

$$\frac{\partial p_{i,j}}{\partial x_{i,k}} = p_{i,j}\left[\alpha_{j,k} - \sum_{z=0}^{2} p_{i,z} \alpha_{z,k}\right]$$

3.4 Endogeneity

Let us denote π as the profit function.

$\pi = F(p, w, q, A)$, where p is the market price vector, w is the input cost vector, q is the quantity produced vector, and A denotes technology adoption.

We assume that technology adoption is an endogenous variable because adoption explains profit, and at the same time, the expected profit also explains adoption. The test of endogeneity (Appendix 3) confirms this assumption.

Therefore, we admit that technology adoption is an endogenous variable that we must replace using instruments. These variables have a direct influence on the decision to adopt but do not depend on profits.

We have $E(\pi) = F(X\beta)$ as the nonlinear adoption function average, where X is the vector of explanatory variables, and β is the coefficient vector.

To take into account the endogeneity hypothesis, we consider unobserved component η that gives rise to endogeneity. We then have the following:

$$E(\pi \mid X, A, \eta) = F(X\beta + A\alpha + \eta\delta) + \varepsilon_1 \text{ and } A = z\varphi + \eta + \varepsilon_2$$

where X = (*price*, *costs*, *quantity*); z = (*instrument*) = (*yield*);ε is the error term with $\varepsilon_1 \sim N(0, \sigma)$ and $\varepsilon_2 \sim logistic(0, \pi^2/3)$.

Because adoption is measured on more than two levels (no adoption, low adoption and strong adoption), we use a multinomial logit model to examine this variable.

The probability of adoption being equal to the value of j is measured as follows:

$$Prob(y_{1i} = j) = \frac{\exp(u(x_i))}{\sum_{k=0}^{2} \exp(u(x_{i,k}))} = \frac{\exp(z_i\alpha_j; \eta_i\alpha)}{1 + \sum_{k=1}^{2} \exp(u(z_{i,k}))}$$

Generalised structural equation models are used to form a nonlinear system with an unobserved component causing endogeneity (Wooldridge, 2010). More accurately, we use a nonlinear instrumental variable and a control functions approach (Blundell et al., 2013; Chesher and Rosen, 2013).

4 Results and discussion

We successively present and discuss the adoption determinants and their effects on profits using different approaches.

4.1 Adoption determinants

According to our estimations, the main positive and significant determinant of soil and water conservation method adoption is the yield as measured by Araya and Asafu-Adjaye (2001). Due to the effect of soil erosion on yields, the authors show with a Tobit model whether farmers are able to use of soil conservation technologies. To a lesser extent, farm size also positively influences technology adoption. Indeed, similar to Anley et al. (2007), the area of cultivated land was found to have a significant effect on the use of soil and water conservation techniques, improving soil bund and cut-off drainage.

The independence of an irrelevant alternative has not been violated as proven in Appendix 1. Table 3 shows that the yield effect on adoption probability is positive. Yield improvement increases the probability of adopting more intensive soil and conservation technologies, which is in agreement with economic theory.

Table 3 Estimation results for adoption on explanatory variables

Adoption	*Multinomial logit*	
	coef.	*P value*
0	(base outcome)	
1		
site	0.1318984	0.662
size	0.0433551	0.783
active persons	–0.3790913**	0.047
off_act	–0.0283397	0.852
yield	0.0043717*	0.069
education	0.3429426	0.740
crop	0.7370181	0.523
crop_yield	–0.0012866	0.312
constant	–2.683298	0.280
2		
site	0.8549925**	0.012
size	0.3833245***	0.033
active_persons	–0.4911695**	0.015
off_act	–0.2474046	0.134
yield	0.0114485***	0.000
education	–0.7693812	0.488
crop	3.587226**	0.037
crop_yield	–0.0039183**	0.014
constant	–12.24484***	0.001
Sample size (*n*)	194	
Prob. > chi^2	0.0000	
Log likelihood (log *L*)	–128.3692	

Notes: (*) denotes significance at 10%, (**) denotes significance at 5%, and (***) denotes significance at 1%.

If we assume that more intensive technologies are synonymous with better yields, we should expect to find a greater preference for a high adoption level. This farmer behaviour is observed from the predicted probabilities.

Table 4 presents the probability of strong technology adoption (adoption = 2) as equal to 51.27% with all predictors are set to their mean values. This value is higher than the values for no and low adoption. For the study sample, farmers are more inclined to intensively adopt sustainable agriculture practices. Adoption (low and high) is greatly preferred (78.19%) to no adoption (21.81%).

Table 4 Predicted probability of adoption level at the means of covariates

	Margin	*P value*
Predict		
Prob (adopt = 0)	0.218147***	0.000
Prob (adopt = 1)	0.269101***	0.000
Prob (adopt = 2)	0.512752***	0.000

Notes: (*) denotes significance at 10%, (**) denotes significance at 5%, and (***) denotes significance at 1%.

To more precisely determine the influence of these determinants on adoption, we evaluate their marginal effects.

Table 5 shows that a change of yield from one change decreases the probability of 'no adoption' and 'low adoption', respectively, by 0.15 and 0.07 percentage points. However, when the yield varies by one unit, the probability of intensively adopting sustainable farming practices increases by 0.22 percentage points.

Table 5 Marginal effects of determinants on technology adoption

Yield	*dy/dx*	*P-value*
1	–0.0015372***	0.000
2	–0.0007198**	0.075
3	0.002257***	0.000
Size	*dy/dx*	*P-value*
1	–0.045422*	0.082
2	–0.0443646	0.130
3	0.0897866**	0.023

Notes: * denotes significance at 10%, ** denotes significance at 5%, and *** denotes significance at 1%.

Despite the relatively small marginal effects found, we find a positive effect on the probability of adoption from an intensive use of these techniques, but we find a negative effect in the other cases. However, the positive marginal effect remains stronger than the negative effect. Thus, by improving yields, farmers tend to intensively increase their propensity to adopt sustainable farming practices and, at the same time, reduce their desire to avoid using such practices or to adopt them a marginal level.

4.2 *Effect of adoption on profits by propensity matching*

The results of the propensity score test are satisfactory and presented in Appendix 4. The balancing property is satisfied; matching is possible; and we use the nearest neighbour matching, radius matching and kernel matching methods.

The average equality test of the different explanatory variables shows no difference in average between the control and counterfactual groups. The results of Table A6 shown in Appendix 5 justify this finding; the property of conditional independence is verified.

The matching estimates show that the effects of adoption on profits are significant and positive regardless of the method used.

The results listed in Table 6 show that the adoption of sustainable agricultural practices has a positive average effect for adopters of orders of 0.878, 0.776 and 0.81 million CFA depending on the estimation method chosen. These results correspond to coefficients of approximately 1.13 to 1.28 times the average investment amount of each farmer.

Table 6 Estimation results by matching method

	Nearest neighbour matching	*Radius matching*	*Kernel matching*
ATT	8.78e+05***	7.76e+05***	8.10e+05***
t	6.711	7.228	8.125
Std. err.	1.31e+05	1.07e+05	99,650.960

Notes: * denotes significance at 10%, ** denotes significance at 5%, and *** denotes significance at 1%.

The multinomial logit approach takes into account the intensity of the adoption of combinations of sustainable agricultural practices. Indeed, as previously defined, the use of these practices is not exclusive and allows the most affluent farmers to combine them at will. According to Baidu-Forson (1999), the availability of short-term benefits is one of the factors that motivates the use of specific soil and water management technologies.

However, the matching approach does not specifically highlight differences by intensity of adoption because treated and control individuals are matched by the propensity score. This gives us, for farmers, an estimate of the average effect of adoption on profits that is much more global than the average effect estimated by the multinomial logit.

All matching estimation methods used show an effect of adoption on profits of less than one million CFA francs. When using a binary approach (matching: adoption or no adoption), the effect on profits is less significant than when considering the level of adoption intensity with the multinomial logit model.

Anim (2008) found that an increase in long-term profits and an awareness of soil erosion problems significantly lead farmers to adopt soil and water conservation methods at the expense of age, the security of land tenure, informal communication, the size of landholding and the difficulty of adopting a particular technology. Thus, in taking into account this difference between the multinomial logit model and matching, when we consider the intensity of adoption (multinomial logit), the average effect of adoption is stronger than when we do not (matching). This result reflects the fact that it is more beneficial for smallholders to adopt sustainable farming practices intensively than to do so moderately. Indeed, if the overall average effect of SAP adoption is less significant than the effect of intensive adoption, this implies that the effect of low adoption would not result in better gains for adopters.

This result corroborates that presented in Table 5, show shows farmers' greater interest in intensively adopting sustainable practices than applying less or no adoption. Unlike Giller et al. (2011), we find that the use of sustainable agricultural practices for smallholder farmers in developing countries is beneficial if they adopt them intensively.

4.3 Effect of adoption on profits by the multinomial logit model

We define adoption as an endogenous variable of the profit equation. To solve this endogeneity problem given the last estimations, we denote the variables ‘adoption’ and farm ‘yield’ as instruments. We present the results with instrumental variables in Table 7. Further details are shown in Appendix 2.

Table 7 Regression of instrumental variables (2SLS)

Profit	*Average marginal effect*	*t*
Adopt	1,144,113***	5.83
Price	38,762.77**	2.35
Quantity	156.8176***	3.82
Age	9,515.14*	1.86
Education	–200,009.4	–0.76
Crop	1,030,811**	2.15
Off_act	59,969.58*	1.67
Active_persons	38,905.6	0.76
Site	–31,740.37	–0.44
Crop_yield	–712.5875***	–5.63
Size	–9,637.626	–0.15
_cons	–1,207,959**	–2.43

Notes: Instrumented: adopt; * denotes significance at 10%, ** denotes significance at 5%, and *** denotes significance at 1%.

The results show that the adoption of anti-erosion practices helps improve, on average, profits by 1.14 million CFA[2] francs at the 1% threshold, i.e., 1.67 times the average investment made per farmer. This may justify farmers’ greater interest in adopting sustainable agricultural practices. Bekele and Drake (2003) shows through a multinomial logit study, that the intensity of the adoption of sustainable agricultural practices is positively related to financial support for initial investment. Thus, a strong initial investment promotes more intensive adoption and induces greater expectations of returns on investment.

The adoption of anti-erosion practices has a direct effect on the ‘yield’, which serves as the instrument for the ‘adoption’ variable in the estimate.

We also find that price and quantity have a positive effect on profits. For Araya and Asafu-Adjaye (2001), engaging in another activity determines soil and water conservation methods and thus positively affects profits. The variable ‘age’ has a positive effect that can be explained by farmers’ experience, which can serve as a significant advantage (Teklewold et al., 2013). This finding is in line with the expected results.

4.4 Scope and implications of results

The adoption of sustainable practices is a panacea for sustainable smallholder farming, as shown by Pan et al. (2021), whose work corroborates our results by showing that a smaller farm size is conducive to the adoption of sustainable practices, especially labour-intensive practices. Indeed, if the size of farms increases, the level of capital and knowledge to be mobilised becomes much greater in the face of financing constraints.

Salaisook et al.'s (2020) work on smallholder rice farmers in Thailand reinforces the conclusions of our work. The authors show that smallholders are in part motivated to adopt sustainable farming practices by the 'step up' strategy of investing in their farms to improve their ability to generate yields and profits over time.

Furthermore, the results obtained through this research highlight that the yield obtained is a major determinant of the dichotomous approach of adopting or not adopting sustainable agricultural practices. However, once the decision to adopt is made, it is the financial capacity of the farmer that determines the intensity of adoption. Thus, our results confirm Thompson et al.'s (2021) finding that motivations behind adoption differ across moderate and intensive levels of adoption. Such results have policy implications.

To achieve the goals of sustainability and farmland protection, policymakers must not only operate levers that encourage smallholder farmers to adopt sustainable practices but also strengthen measures that ensure the sustainability of such approaches through, among other vehicles, access to finance.

5 Conclusions

The objective of this research was to identify the determinants of the adoption of sustainable agricultural practices and to assess their effects on potential benefits.

The major determinant that can motivate actors to adopt is yield improvement. From this perspective, many farmers are willing to improve their yields. The size of the farm is also found to have a positive influence on adoption.

The adoption of sustainable farming practices by farmers is proving to be a beneficial practice for smallholder systems in Sub-Saharan Africa. The use of these practices has a positive effect on returns and profit. However, these results must be qualified according to the intensity of adoption. Intensive adoption leads to better average gains than no or low adoption. This finding raises the issue of credit constraints for farmers. Indeed, the intensification of adoption requires a significant investment by smallholders, which does not guarantee their commitment. Thus, in terms of public policy, it is a matter of encouraging the intensification of the adoption of sustainable agricultural practices for the gains they provide but also for the protection of the soil they cause. However, the success of such a policy depends on investment credit to support smallholders. Our results, however, must be contextualised to the arid study area examined and our small sample size.

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Notes

1 The National Institute of Environment and Agricultural Research (NIEAR).

2 1 US dollar ≈ 500 CFA francs.

Appendix 1

Table A1 Test of independence of irrelevant alternatives

suest m*, noomitted

Simultaneous results for m1, m2, m3

Number of obs. = 194

	Robust		*z*	*P > |z|*	*[95% conf. interval]*	
	Coef.	*Std. err.*				
m1_0						
site	–0.85499***	0.3301036	–2.59	0.010	–1.501984	–0.2080014
size	–0.383324*	0.1983978	–1.93	0.053	–0.772177	0.0055279
active persons	0.49117**	0.246731	1.99	0.047	0.0075857	0.9747534
yield	–0.01145***	0.0034021	–3.37	0.001	–0.0181165	–0.0047804
crop	–3.58722**	1.768247	–2.03	0.042	–7.052927	–0.1215246
crop_yield	0.00392**	0.0017628	2.22	0.026	0.0004634	0.0073733
sec_act	0.2474046	0.1796672	1.38	0.169	–0.1047366	0.5995458
education	0.7693812	0.8955843	0.86	0.390	–0.9859318	2.524694
_cons	12.24484	3.898635	3.14	0.002	4.603654	19.88602

Notes: *Denotes significance at 10%, **denotes significance at 5% and ***denotes significance at 1%.
.test [m1_1 = m2_1], cons notest.
.test [m1_0 = m3_0], cons acc.
chi2(3) = 0.08.
Prob. > chi2 = 0.9944.

Table A1 Test of independence of irrelevant alternatives (continued)

	Robust		*z*	*P > |z|*	*[95% conf. interval]*	
	Coef.	*Std. err.*				
m1_1						
site	–0.72309**	0.3223829	–2.24	0.025	–1.354953	–0.0912353
size	–0.339969*	0.1804427	–1.88	0.060	–0.6936307	0.0136917
active persons	0.1120782	0.1772234	0.63	0.527	–0.2352733	0.4594297
yield	–0.0071***	0.0020812	–3.40	0.001	–0.0111559	–0.0029976
crop	–2.850208*	1.546608	–1.84	0.065	–5.881504	0.1810891
crop_yield	0.00263**	0.0011234	2.34	0.019	0.0004299	0.0048336
sec_act	0.2190649	0.1592312	1.38	0.169	–0.0930224	0.5311523
education	1.112324	0.8804346	1.26	0.206	–0.6132964	2.837944
_cons	9.56154	3.507572	2.73	0.006	2.686826	16.43626
m1_2						
m2_0						
site	–0.85499**	0.3301036	–2.59	0.010	–1.501984	–0.2080014
size	–0.383324*	0.1983978	–1.93	0.053	–0.772177	0.0055279
active persons	0.49117**	0.246731	1.99	0.047	0.0075857	0.9747534
yield	–0.0114***	0.0034021	–3.37	0.001	–0.0181165	–0.0047804
crop	–3.58722**	1.768247	–2.03	0.042	–7.052927	–0.1215246
crop_yield	0.00392**	0.0017628	2.22	0.026	0.0004634	0.0073733
sec_act	0.2474046	0.1796672	1.38	0.169	–0.1047366	0.5995458
education	0.7693812	0.8955843	0.86	0.390	–0.9859318	2.524694
_cons	12.24484	3.898635	3.14	0.002	4.603654	19.88602
m2_1						
site	–0.72309**	0.3223829	–2.24	0.025	–1.354953	–0.0912353
size	–0.339969*	0.1804427	–1.88	0.060	–0.6936307	0.0136917
active persons	0.1120782	0.1772234	0.63	0.527	–0.2352733	0.4594297
yield	–0.0071***	0.0020812	–3.40	0.001	–0.0111559	–0.0029976
crop	–2.85021**	1.546608	–1.84	0.065	–5.881504	0.1810891
crop_yield	0.00263**	0.0011234	2.34	0.019	0.0004299	0.0048336
sec_act	0.2190649	0.1592312	1.38	0.169	–0.0930224	0.5311523
education	1.112324	0.8804346	1.26	0.206	–0.6132964	2.837944
_cons	9.56154	3.507572	2.73	0.006	2.686826	16.43626
m2_2						

Notes: *Denotes significance at 10%, **denotes significance at 5% and ***denotes significance at 1%.
.test [m1_1 = m2_1], cons notest.
.test [m1_0 = m3_0], cons acc.
chi2(3) = 0.08.
Prob. > chi2 = 0.9944.

Table A1 Test of independence of irrelevant alternatives (continued)

	Robust		*z*	*P* > |*z*|	*[95% conf. interval]*	
	Coef.	*Std. err.*				
m3_0						
site	–0.85499**	0.3301036	–2.59	0.010	–1.501984	–0.2080014
size	–0.383324*	0.1983978	–1.93	0.053	–0.772177	0.0055279
active persons	0.49117**	0.246731	1.99	0.047	0.0075857	0.9747534
yield	–0.0114***	0.0034021	–3.37	0.001	–0.0181165	–0.0047804
crop	–3.58722**	1.768247	–2.03	0.042	–7.052927	–0.1215246
crop_yield	0.00392**	0.0017628	2.22	0.026	0.0004634	0.0073733
sec_act	0.2474046	0.1796672	1.38	0.169	–0.1047366	0.5995458
education	0.7693812	0.8955843	0.86	0.390	–0.9859318	2.524694
_cons	12.24484	3.898635	3.14	0.002	4.603654	19.88602
m3_1						
site	–0.72309**	0.3223829	–2.24	0.025	–1.354953	–0.0912353
size	–0.339969*	0.1804427	–1.88	0.060	–0.6936307	0.0136917
active persons	0.1120782	0.1772234	0.63	0.527	–0.2352733	0.4594297
yield	–0.0071***	0.0020812	–3.40	0.001	–0.0111559	–0.0029976
crop	–2.85021**	1.546608	–1.84	0.065	–5.881504	0.1810891
crop_yield	0.00263**	0.0011234	2.34	0.019	0.0004299	0.0048336
sec_act	0.2190649	0.1592312	1.38	0.169	–0.0930224	0.5311523
education	1.112324	0.8804346	1.26	0.206	–0.6132964	2.837944
_cons	9.56154	3.507572	2.73	0.006	2.686826	16.43626
m3_2						

Notes: *Denotes significance at 10%, **denotes significance at 5% and ***denotes significance at 1%.
.test [m1_1 = m2_1], cons notest.
.test [m1_0 = m3_0], cons acc.
chi2(3) = 0.08.
Prob. > chi2 = 0.9944.

Appendix 2

Table A2 Detailed results of the instrumental variables (2SLS) regression

Instrumental variables (2SLS) regression				*Number of obs. = 194*		
				Wald chi²(11) = 243.01		
				Prob. > chi² = 0.0000		
				R-squared = 0.4115		
				Root MSE = 7.4e+05		
Profit	*Coef.*	*Std. err.*	*z*	*P > |z|*	*[95% conf. interval]*	
adopt	1,144,113***	196,170.4	5.83	0.000	759,626	1.528,600
price	38,762.77**	16,470.57	2.35	0.019	6,481.053	71,044.5
quantity	156.8176***	41.02048	3.82	0.000	76.4189	237.2162
age	9,515.14*	5,126.671	1.86	0.063	–532.9509	19,563.23
education	–200,009.4	264,123	–0.76	0.449	–717,681.1	317,662.3
crop	1,030,811**	478,707.8	2.15	0.031	92,561.42	1,969,062
sec_act	59,969.58*	35,937.95	1.67	0.095	–10,467.51	130,406.7
Active persons	38,905.6	50,924.25	0.76	0.445	–60,904.09	138,715.3
site	–31,740.37	71,992	–0.44	0.659	–172,842.1	109,361.4
crop_yield	–712.5875***	126.4805	–5.63	0.000	–960.4847	–464.6903
size	–9,637.626	62,701.91	–0.15	0.878	–132,531.1	113,255.9
_cons	–1.03e+07	4,236,651	–2.43	0.015	–1.86e+07	–2,007,183

Notes: Instrumented: adopt.
Instruments: price, quantity, age, education, crop, off_act, active persons, site, crop_yield, size, and yield.
*Denotes significance at 10%, **denotes significance at 5% and ***denotes significance at 1%.

Appendix 3

Table A3 Tests of endogeneity

Ho: the variables are exogenous
Durbin (score) chi²(1) = 35.8927 (p = 0.0000)
Wu-Hausman F(1,184) = 41.0896 (p = 0.0000)

Appendix 4

Table A4 Estimated propensity score in the region of common support

The region of common support is [0.16725872, 0.99993334]		
Description of the estimated propensity score in the region of common support		
Estimated propensity score		
Percentiles	*Smallest*	
1%	0.1829545	0.1672587
5%	0.2067169	0.1829545
10%	0.2346187	0.1870598
25%	0.4361916	0.1905791
50%	0.7405217	
	Largest	
75%	0.9654256	0.9993613
90%	0.9962601	0.9996696
95%	0.9985692	0.9998644
99%	0.9998644	0.9999333
Obs.	178	
Sum of wgt.	178	
Mean	0.6775308	
Std. dev.	0.2900149	
Variance	0.0841087	
Skewness	–0.3739184	
Kurtosis	1.604591	

Note: The common support option has been selected.

Step 1 Identification of the optimal number of blocks.

The final number of blocks is 5.

This number of blocks ensures that the mean propensity score is not different for treated and controls in each block.

Step 2 Test of balancing property of the propensity score.

The balancing property is satisfied.

Table A5 Distribution of observations by region of common support

Inferior of block of p-score	*Adopted*		
	0	*1*	*Total*
0.1672587	4	3	7
0.2	27	9	36
0.4	16	12	28
0.6	4	20	24
0.8	5	78	83
Total	56	122	178

Note: The common support option has been selected.

Appendix 5

Table A6 Difference test of averages before and after matching

Variables	*t*	*Std. err.*	*p-value*
price	0.9567	2.12333	0.3400
quantity	0.6870	0.7109972	0.4923
age	0.1289	2.148104	0.8976
education	0.4966	0.0406734	0.6201
crop	–0.9490	0.0774249	0.3439
off_act	0.3634	0.2593978	0.7168
active persons	–0.6952	0.2210727	0.4879
site	–0.0238	0.1477606	0.9811
crop_yield	0.5840	2.338234	0.3546
size	–0.7971	0.2631259	0.4264
yield	0.6529	1.073763	0.4701