Impact of Sustainable Land Management Technologies adoption on maize farmers' well-being in North East Benin

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Abstract

Sustainable Land Management (SLM) plays an important role in balancing human demands and ecosystem services of available natural resources. It improves food security, reduces the risk of conflict and supports adaptation to climate change. This study examines the impact of Sustainable Land Management Technologies (SLMTs) adoption on yield, profit, and labor productivity of smallholder farmers in North East of Benin. The study uses primary data from smallholder farmers through a three-level stratified random sampling of 431 maize farmers and the Local Average Treatment Effect (LATE) model to account for selection bias and endogeneity. We used Instrumental Variable Estimators to estimate the LATE of SLMTs adoption on yield, profit and labor productivity. We studied four SLMT, namely cattle manure (CM), *Mucuna pruriens* (MP), pigeon pea (PP), and crop residue management (CR). The results showed that SLMTs adoption increased maize yield, labor productivity and profit. Promotion of these technologies should consider heterogeneous conditions, agroecological environments and farmers' characteristics, including the resources available at the farm level.

Keywords: Sustainable Land Management, Yield, Average Labor Productivity, Local Average Treatment Effect, North East Benin

INTRODUCTION

Land degradation is one of the challenges in sub-Saharan Africa (Diao and Sarpong, 2011), especially in Benin (Avakoudjo *et al*., 2013; Kombienou *et al*., 2015). There are two causes: exogenous and endogenous factors. The exogenous causes are related to the natural conditions of the environment and climatic, topographical, and biophysical conditions. On the other hand, endogenous factors relate to inappropriate agricultural practices (slash-and-burn cultivation), population growth, land tenure insecurity. This degradation is the cause of the decline in yield with very significant negative impacts on farmers. The agricultural sector in Benin is more of a subsistence agriculture. Therefore, SLMTs are effective techniques to contribute to improving income and the reduction of food insecurity. So, there is a widespread use of SLMTs to combat land degradation and thus as a mechanism to increase land productivity (Martey *et al*., 2019). It also improves agricultural incomes (Martey *et al*., 2019) and ensures food security (Kim *et al*., 2019; Nkomoki *et al*., 2018; Sileshi *et al*., 2019). While SLMTs are not a panacea, they represent a way out for many farmers facing land degradation.

While environmental science is attempting to understand the potential impact of introducing SLMTs on soil quality and structure (Bell *et al*., 2018; Cherubin *et al*., 2019), on soil organic carbon (Thierfelder *et al*., 2015), social science has taken an interest in adoption and dissemination challenges, leading to low adoption rates (Adesina *et al*., 2000; Cavane, 2016; Mugwe *et al*., 2009; Ngwira *et al*., 2014; Vidogbéna *et al*., 2016) and social and economic impacts (Kassie *et al*., 2015; Manda *et al*., 2016). In recent years, the literature provides several methods to analyze the social and economic impact of SLMTs adopted. We have econometric methods, economic surplus production methods, and more holistic household modeling. Econometric impact assessment methods refer to experimental or non-experimental methods (NEM). Among experimental methods, there are randomization or random control trial (RCT) and natural experiment. Duflo *et al*. (2008) conducted a randomized experiment to investigate the effects of chemical fertilizer use on farmers' yields and incomes in Kenya. This randomized experiment is one of the few in the field of soil fertility management and demonstrates the difficulty of having experimental data in practice. In general, economists mainly use NEM based on economic and econometric theories. The use of non-experimental data is widespread (Kim *et al*., 2019; Sileshi *et al*., 2019). They include the double difference method, matching methods that posit that the effects might be related to observable factors, essentially propensity score matching (PSM), instrumental variables, selection very close to instrumental variables, the endogenous switching regression model (ESR), which posits that the effects could be associated with phenomena that are not observable. All of these methods receive criticism for their weaknesses. Moreover, they sequentially address the shortcomings observed in each. However, NEM, PSM (Etsay *et al*., 2019; Martey *et al*., 2019; Sileshi *et al*., 2019) and ESR (Asfaw *et al*., 2016; Martey *et al*., 2019; Sileshi *et al*., 2019) are the most commonly used in adoption studies of SLMTs. Given the shortcomings of these methods, a combination limits the estimation bias that occurs. Therefore, we assume that the impact is based first on observable variables and second step on unobservable variables. For example, several impact studies on SLMT adoption have combined PSM and ESR (Martey *et al.*, 2019; Sileshi *et al.*, 2019) or PSM with instrumental variables (Amare *et al.*, 2012).

In Benin, most studies have assessed the level of performance of farmers' SLMT adoption (Adebiyi *et al.*, 2019; Adégbola *et al.*, 2002; Biaou *et al.*, 2016; Degla, 2012; Yabi *et al.*, 2016). Few impact assessments studies on SLMTs exist. Other studies have assessed their effects using NEM (Adégbola and Adékambi, 2006). This study assesses the impact of SLMTs adoption on maize yield, profit, and labor productivity in north-eastern Benin. We contribute to the soil economic literature by filling some existing gaps. First, previous studies, except the study of Hörner and Wollni (2022), were limited to yields, total production, and income (Asfaw *et al.*, 2016; Etsay *et al.*, 2019; Kassie *et al.*, 2015) without addressing labor productivity. However, the adoption of SLMT increases the workload on the plots. Second, we use a LATE to collectively account for selection bias, heterogeneity, and endogeneity of impact, and to compare the three outcome indicators considered by technology. To our knowledge, no econometric study has used this model in the field of soil fertility management in Benin to assess the impact of SLMTs adoption. Finally, we address the gender inequalities observed in SLMTs adoption through the interaction of specific gender variables. No gender econometric study on the impact of adopting multiple technologies on soil fertility management exists in Benin. In this regard, this article contributes to the literature on gender in technology adoption. From a policy perspective, this study will help propose policy tools to facilitate the scaling up adoption of SLMTs. The rest of the article is structured as follows. The second section deals with the background and the third section with the theoretical and empirical framework of the study. Section four highlights the results and discussion. This article ends with a conclusion with political implications.

MATERIALS AND METHODS

Study area

We conducted this research in Agricultural Development Hub 2 (ADH 2), in North East Benin in Agroecological Zone 2. It extends between latitudes N 1000' and N 1120' and longitudes E 120' and E 400'. The study included only south of Alibori and north of Borgou among the three regions covered by PDA 2: Alibori (South), Borgou (North) and 2KP (Kandi-Kouandé-Péhunco). The climate in the area is Sudanese, with two seasons (one rainy and one dry season). The rainiest period is from July to September. During these months, the daytime temperature is around 30/32 °C. The dominant soils in the target area are ferritic and ferrous. These soils have low fertility but good physical and poor chemical properties (Amonmide *et al.*, 2019). Around 80% of soils have below-average fertility (Adégbola *et al.*, 2018). Consequently, total fertility is low, threatening the viability of the production system. Indeed, this level of soil fertility combined with widespread chemical use degrades the soil leading to deficiencies in organic matter, phosphate, nitrogen, cation exchange capacity, and exchangeable bases. Although maize, sorghum, and rice are the most widespread food crops in the ADH2. It is also the most cotton-growing region in the country. In addition, farmers make extensive use of animal traction due to the large number of herders (Adégbola *et al.*, 2018).

Data collection

We collected data using a three-level stratified random sampling design. At the first level, we selected three (3) communes, one per homogeneous subregion of ADH 2 (ADSH), as follows: Kandi in ADSH 1, Gogounou in ADSH 2, and Bembérèké in ADSH 3. We then performed a weighting based on the weight and number of intervention villages in each community. This weighting led us to 6 villages in Bembérèké, 7 in Gogounou, and 6 in Kandi. The third level was the determination of the number of farmers. Farmers of the treated group consist of all ProSOL farmers who have benefited from the project for at least five years. Starting from a list we received from ProSOL containing 1386 farmers that meet this criterion, we performed a simple random sampling using (Yamane, 1967) formula $[X = N/[1 + N(e)^2]$, with X as the minimum sample size, N as the population size, and e as the level of precision. This leads to a minimum of 287 farmers for the treated group. Based on the number of farmers treated in each village, we conducted the selection to a sample of 287 farmers from all 19 studied villages. In addition, we constituted a control group of 144 farmers based on the same methodology used to choose treated group.

Modeling the heterogeneous effect of SLMTs adoption

The theoretical framework underlying this study combines both the production theory and the latent variable discrete choice model for selection into treatment. They provide a framework for combining economic theory and "structural econometric analysis" in causal treatment effects evaluation (Heckman and Vytlacil, 2007). Accordingly, the targeted farm performance outcomes are modelled in terms of their determinants as specified by production theory. In this framework, is the observed farm performance outcome variables, here profit, yield and labor productivity, for a given farmer *i*. A maize farmer is observed to have five hypothetical potential outcomes $Y_{(0,t)}$ with t={1,...,4} SLMTs, representing its potential outcome with and without adoption of one of SLMTs. Following Carneiro *et al.*, (2003) and Heckman and Vytlacil (2007), we model each potential performance outcome conditioning to variables as follows:

$$Y_0 = X_0\beta_0 + U_0 \quad (1)$$

$$Y_t = X_t\beta_t + U_t \quad (2)$$

Where $X_{(0,t)}$ is the observed characteristics of various farms and farmers, such as the management practices of farmer including managerial characteristics such as adoption status of SLMTs (Solís *et al.*, 2007), socio-economic and demographic characteristics and the characteristics of the maize production environment; $\beta_{(0,t)}$ are coefficients to be estimated and $U_{(0,t)}$ is the stochastic term which captures the unobserved characteristics. It fulfilled the condition $E[U_{(0,t)}|X_i]=0$.

Moreover, we assume that the potential outcomes can be inferred by a latent variable A_t^*. The adoption decisions process is expressed as follows:

$$A_t^* = \mu_A(t, 0, X_t, Z_t) - V_t \quad (3)$$

$$\text{with } A_t = \begin{cases} t & if \quad A_t^* > 0 \\ 0 & if \quad A_t^* \leq 0 \end{cases}$$

Where X_t and Z_t are observed variables affecting the adoption of the SLMTs. The covariates are common with the outcome equations (1) and (2), while one or more variables C are excluded from the latter; $\mu_A(t,0,X_t, Z_t)$ is the deterministic component and is an i.i.d. error term indicating unobserved heterogeneity in the propensity for treatment. A^*_t is interpretable as the net gain from adoption decision of an SLMTt. For the same farmer, we observe the performance outcomes, $Y_{(0,t)}$ associated with adoption of SLMTs which can be written in form of switching regression model as:

$$Y_{(0,t)} = Y_0 + (Y_1 - Y_0)t_1 + (Y_2 - Y_0)t_2 + (Y_3 - Y_0)t_3 + (Y_4 - Y_0)t_4 \quad (4)$$

where the subscripts indicate the adoption and non-adoption status of SLMTs. The equation (4) is a variant of the Rubin, (1974) "potential outcomes framework" (Heckman *et al.*, 2007). The effect of the adoption of an SLMTs on performance outcomes is the differential farmer's performance outcomes between the adoption and non-adoption decisions of the SLMTs and is given by $\Delta_t = Y_t - Y_0 \; t \neq 0$ (Carneiro *et al.*, 2003b; Heckman and Vytlacil, 2007). Two treatment effect parameters receive lot of attention in the literature for binary treatments (Greenland *et al.*, 1999; Manski, 1996; Rosenbaum and Rubin, 1983). The first one Average Treatment Effect (*ATE*) and its variant conditional Average Treatment Effect (*ATE*| x). is defined as the expected effect of treatment on a randomly drawn person from the population. Its variant is estimated for subpopulation with given observed characteristics $X_t = x_t$. The second parameter is the average treatment effect on adopters and its variant conditional Average Treatment Effect on treated (*ATE*1| x). The latter estimates how those individuals with observed characteristics $X_t = x_t$ that are currently adopted the SLMT benefit from them on average (Cornelissen *et al.*, 2016). Other treatment effect parameters such as the marginal treatment effect (MTE) and the local average treatment effect (LATE) are found in the binary treatment literature (Cornelissen *et al.*, 2016; Wooldridge, 2004).

The potential outcomes model in Eq. (4) is related to structural econometric model as follows (Heckman, 2007):

$$Y_t = \delta + X\gamma + A_t\widetilde{X}_t\lambda + A_t\overline{\eta}_t + A_t\widetilde{\eta}_t + \varepsilon_t \quad (5)$$

where δ is the constant of the model, X is the vector of pretreatment explanatory variables that have potential influence on $Y_{(0,t)}$; $\gamma=\beta_0$, $\lambda=\beta_t-\beta_0$, $\eta_t=U_t-U_0$ and $\varepsilon_t=U_0$; $\bar{n}_t=E[\eta_t]$ is the mean of η_t; $\tilde{n}_t=\eta_t-E[\eta_t]$ is the deviation of η_t from its mean; $A_t\tilde{n}_t+\varepsilon_t$ is a composite error term; $\widetilde{X_t} = X - \overline{X}$ is demeaned of both pretreatment and post treatment explanatory variables; $Y_{(0,t)}$ is a continuous random variable (Carneiro *et al.*, 2003b; Heckman *et al.*, 2007). The OLS estimator of the adoption effect of a given SLMT$_t$ yield the expected effect Δ_t conditional on x written as:

$$E(\Delta_t|X) = \widetilde{X}_t\lambda + \overline{\eta}_t + E(A_t\widetilde{\eta}_t + \varepsilon_t) \quad (6)$$

The expected effect Δ_t conditional on x is composed of the observable heterogeneity $(\widetilde{X}_t\lambda)$ which is the *ATE(X)*, the idiosyncratic gain $(\tilde{n}_t)$ derived from SLMT adoption referred to as unobserved heterogeneity and a composite error (Heckman, 1997). The unobserved heterogeneity is responsible for the variation of the effect of SLMT adoption across maize farms. The identification of the equation (5) and therefore that of the effect parameters and their estimation methods depend to the unobserved heterogeneity and the presence of the element $A_t\tilde{n}_t$ in the composite error $A_t\tilde{n}_t+\varepsilon_t$. These two last elements represent the bias caused by the selection into treatment based on the potential farm performance outcomes when OLS is applied for estimation.

This study assumes that the effects of adopting SLMT will vary among maize farmers. A farmer's decision to adopt a given SLMT is determined by the positive net expected gain A_t^*, resulting from adoption (Adegbola, 2010; Dimara and Skuras, 2003; Wooldridge, 2002). This implies that $U_t \neq U_0$ and therefore the outcomes $Y_{(0,t)}$ are generated by different unobservables (Cornelissen *et al.*, 2016). The conditional expected value of $A_t\tilde{n}_t$ given (X_t,Z_t) can be written as follows:

$$E(A_t\widetilde{\eta}_t|X_t\,Z) = E(\widetilde{\eta}_t|A_t = 1, Z)Pr(A_t = 1|\,Z) \quad (7)$$

Because of the adoption of ISFM technologies is based on the unobserved idiosyncratic gain, the term $E(\tilde{n}_t)|\,A_t=1, Z)\neq 0$ in Eq. (7) is different from zero. Consequently, the conditional expected value of $A_t\tilde{n}_t$ given (X_t,Z_t) is different from zero. Any instrument Z_t that affects A_t will in this case also be correlated with the composite error term $(A_t\tilde{n}_t+\varepsilon_t)$. Standard instrumental estimation of Eq. (5) will therefore yield a biased estimate of the expected effect of adopting the SLMTs, conditional on x. The local average treatment effect (LATE) is identified and estimated by IV with a binary instrument when the treatment effects are heterogeneous and selection into treatment is based on a partial or a full knowledge of the idiosyncratic gain derived from treatment (Angrist and Imbens, 1995; Vella and Verbeek, 1999; Wooldridge, 2007; Wooldridge, 2002). Angrist and Imbens, (1995) and Angrist *et al.* (1996) clarified the interpretation of IV estimates when treatment effects are heterogeneous (Cornelissen *et al.*, 2016).

A LATE of SLMTs adoption effects on farms' performance outcomes

Following Awotide *et al.*, (2013), the LATE parameter was consistently estimated using both Wald and LARF estimators of LATE developed by Angrist and Imbens, (1995) and Abadie (2003), respectively. LATE parameter gives the adoption effect only for the compliers c-i-e farmers who decide to adopt SLMTs because they heard about them. To implement LATE, we suppose there exists a single binary instrument variable Z_i with $Z_i=1$ if the farmer heard about the SLMT and $Z_i= 0$ otherwise. We also suppose that Z_i is relevant, valid and does not directly affect the farm performance outcomes (Huber and Wüthrich). In addition, we assume that the instrument is randomly assigned to farmers, after conditioning on observed characteristics . The conditional Local Average Treatment Effect (LATE) is defined by:

$$\begin{aligned} LATE(X) &= E[Y_t - Y_0|A_t > A_0, X_t = x] \\ &= \theta + E[\widetilde{\eta}_i|A_t > A_0, X_t = x] \quad (8) \end{aligned}$$

The Wald estimator of Eq. (8) requires only the observed performance outcomes $Y_{(0,t)}$ variable in Eq. (5), the adoption status variable A_t and the instrument Z. Under assumptions of independence and exclusion of instrument Z, existence of a first stage, and monotonicity, the consistent estimate of LATE using its sample analog is expressed as follows:

$$\widehat{WALD}(X) = \left(\frac{\sum_{i=1}^{n} Y_{(0,t)}Z}{\sum_{i=1}^{n} Z} - \frac{\sum_{i=1}^{n} Y_{(0,t)}(1-Z)}{\sum_{i=1}^{n}(1-Z)}\right) X \left(\frac{\sum_{i=1}^{n} A_t|Z}{\sum_{i=1}^{n} Z} - \frac{\sum_{i=1}^{n} A_t|(1-Z)}{\sum_{i=1}^{n}(1-Z)}\right)^{-1} \quad (9)$$

The Wald estimator will fail to estimate consistently the LATE parameter if the instrument variable is not fully independent of the potential outcomes $Y_{(0,t)}$. Thus, under assumptions of conditional independence assumption (CIA), we use the local average response function (LARF) to recover the LATE:

$$LARF = E\left[Y_{(0,t)}|X_t, A_t > A_0\right] \quad (10)$$

Abadie (2003) shows that under previous conditions, the LARF parameter is mathematically expressed as follows:

$$E\left[g\left(Y_{(0,t)}, A_t, X_t\right)|X_t, A_t > A_0\right] = \frac{1}{P(A_t > A_0|X_t)} E\left[\kappa \cdot g\left(Y_{(0,t)}, A_t, X_t\right)|X_t\right] \quad (11)$$

with $\kappa = 1 - \frac{A_t(1-Z)}{P(Z=0|X)} - \frac{(1-A_t)Z}{P(Z=1|X)}$, the pseudo complier weight and $P(A_t > A_0|X_t)$ is the proportion of compliers in the sample.

where $g(\cdot)$ is a measurable real function of $(Y_{(0,t)}, A_t, X_t)$ with a finite first moment and weighting functions[1]. The estimation involves two-step procedure. In the first step the pseudo weights is calculated using the instrument propensity score $P(A_t = 1|X_t = x)$ of assignment to adoption status. In this study it is generated from a probit model, $P(Z=1|X_t) = \Phi(X_t\gamma)$ where Φ is the cumulative normal distribution. In the second step we estimate $g(Y_{(0,t)}, A_t, X_t)$. If is the parameter vector of $g(Y_{(0,t)}, A_t, X_t)$, they are estimated by equation as follows:

$$\theta_0 = arg \min_{\theta \in \Theta} E\left[\kappa\left(Y_{(0,t)} - g\left(Y_{(0,t)}, A_t, X_t\right)\right)^2\right] \quad (12)$$

The parameter vector, is estimated by a weighted least square method (LS) that minimizes the sample analog of Eq. (12) as follows:

$$\hat{\theta} = arg \min_{\theta \in \Theta} \frac{1}{n} \sum_{1}^{n} E\left[\kappa \left(Y_{(0,t)} - g(A_t, X_t; \theta)\right)^2\right] \quad (13)$$

where $\kappa = 1 - A_t(1-Z)/\left(1 - P(Z|X_t = x)\right) - (1 - A_t)Z/P(Z|X_t = x)$. Abadie, (2003) proves that the resulting estimator of θ is consistent and asymptotically normal. Because of the heterogeneous response of adoption of SLMTs, we assume in this study a nonlinear functional form, specifically an exponential conditional mean performance outcome responses' function. Once, θ is estimated, equation (13) is used to recover the conditional mean treatment effect as a function of . The conditional LATE is then obtained by averaging across x using equation (11). The LATE parameter was consistently estimated separately for each SLMT.

[1] *see Awotide et al., (2013) for details on the function g(·)*

Descriptive statistics of the variables introduced in the model

Table 1 presents the descriptive statistics of the variables used in the impact models. It shows the mean and standard deviation of each variable for adopters and non-adopters of SLMTs. 70% of farmers who did not adopt SLMT are men. 73% of farmers using CM and PP are males. 57% and 56% of those using CR and MP, respectively, are males. There is a significant gender gap between CR adopters and non-adopters. On average,

Tableau 1: Descriptive statistics of the variables of the impact equations

	Non-adopters	CM		PP		CR		MP	
	Mean E-T)	Mean (E-T)	Test	Mean (E-T)	Test	Mean (E-T)	Test	Mean (E-T)	Test
Gender (1=male, 0=female)	0.70(0.45)	0.73(0.44)	-0.059	0.73(0.44)	-0.062	0.57(0.50)	0.15***	0.56(0.51)	0.119
Age (year)	43.7(10.2)	44.7(9.39)	-1.12	40.3(7.31)	3.653**	44.2(11.35	-0.621	45.5(10.7)	-1.815
Education (1=Yes, 0=No)	0.17(0.38)	0.22(0.41)	-0.042	0.23(0.43)	-0.058	0.16(0.37)	0.019	0.12(0.34)	0.058
Zone (1=Cotton zone, 0=non-Cotton zone)	0.73(0.44)	0.85(0.35)	-0.120*	0.53(0.56)	0.233***	0.79(0.46)	-0.059	0.87(0.34)	-0.135
Use of chemical fertilizer (1=Yes, 0=No)	0.89(0.30)	0.90(0.30)	-0.007	0.85(0.35)	0.04	0.87(0.33)	0.022	1(0)	-0.108*
Amount of fertilizer (1=more, 0=less)	0.53(0.49)	0.19(0.41)	0.345***	0.53(0.56)	-0.023	0.56(0.49)	-0.064	0.50(0.56)	0.008
Type of seed used (1=local, 0=improved)	0.93(0.24)	0.75(0.43)	0.179***	0.91(0.28)	0.007	0.97(0.16)	-0.06	0.87(0.34)	0.045
Soil fertility level (1=very fertile, 2=not very fertile, 3=poor)	2.00(0.29)	2.05(0.31)	-0.04	1.93(0.35)	0.07*	2(0.16)	0.008	1.93(0.25)	0.072
Participation in SLMT project (1=Yes, 0=No)	0.66(0.47)	0.88(0.31)	-0.22***	0.96(0.18)	-0.32***	0.64(0.48)	0.045	1(0)	-0.33***
Farmer Group Organization (FGO) (1=Yes, 0=No)	0.42(0.49)	0.44(0.52)	-0.0005	0.55(0.53)	-0.130*	0.48(0.49)	0.0001	0.47(0.52)	0.001
Quantity of Urea (kg/ha)	54.5(37.4)	46.2(24.9)	8.29*	41.3(28.4)	13.41**	53.9(39.4)	-0.23	53.3(29.2)	0.39
Quantity of NPK (kg/ha)	112.8(60.1)	91.1(44.4)	21.65**	121(65.5)	-11.20	121(65.5)	-11.20	112(59.8)	-1.48
Quantity of herbicide (kg/ha)	3.28(1.57)	3.21(1.26)	0.071	3.16(1.28)	0.123	3.38(1.69)	-0.121	3.63(1.42)	-0.373
Quantity of labor (man-day/ ha)	28.1(23.4)	25.5(22.7)	2.63	32.5(33.6)	-5.06	33.7(30.7)	-7.00**	27.4(19.5)	0.54
Total income (FCFA/ha)	311817 (171096)	339670 (138245)	- 22696	346874 (144190)	-30117	317555 (139709)	1900	336845 (108514)	-18394
Yield (kg/ha)	2094 (1004)	2217(827)	-125**	2200 (880)	-103.9*	2000 (778)	125**	2250 (698)	-151
Labor productivity (FCFA/man-day)	1256 (590)	2472(104)	-1215*	2614 (677)	-1348	2013 (279)	279**	2731 (356)	-1411
Profit (FCFA/ha)	143100 (8070)	157339 (19175)	-14238	167486 (23325)	25003*	147745 (16676)	-3960	162359 (24502)	-18594

sd: standard deviation, *: Significant at the 10% level; **: Significant at the 5% level; *: Significant at the 1% level.*

non-adopters are 43 years old. For adopters, the highest average age for MP adopters is 44 years. Overall, at least 12% of farmers are educated, and more than half are in North Benin's cotton zone. The data shows that 0.89% of farmers who do not use SLMTs use chemical fertilizers. At the 10% threshold, there is a significant difference between the use of chemical fertilizers by MP adopters and non-adopters. More than half of all the farmers have already participated in an SLM project. In addition, less than half of non-adopters do not belong to farmers' group organizations (FGO). The performance indicators were per hectare for each group. We observe a significant difference in maize yield, labor productivity, and profit between SLMTs adopters and non-adopters.

RESULTS

Impact of SLMTs adoption maize yield and its determinants

Table 2 presents the results of the impact of the adoption of SLMTs on maize yield. The results indicate a positive impact of SLMTs adoption. LATE estimates suggest that adopting CM, PP, CR, and MP increases yield by 20.9%, 8.7%, 12.8%, and 2.7%, respectively. These proportions correspond to the average changes in performance due to the adoption of these SLMTs. Table 2 presents also the determinants of maize yield given by local average response functions (LARF). This is evidence that apart from a change in SLMTs, other socioeconomic variables significantly explain the variation observed. These factors are age, sex, the quantity of herbicide, labor, NPK, urea, type of seed used, soil fertility level, production area, participation in an SLM project, and the quantity of fertilizer used.

Moreover, several coefficients for the interaction terms are statistically significant. That confirms the heterogeneity of the impact of SLMTs adoption on yield. The F-statistics of the four impact models for the joint significance of the interactive terms indicate that they are statistically significant and different from zero. At the level of the CM adoption impact model on yield, the coefficients of age, herbicide quantity, labor quantity, NPK quantity, Urea quantity, production area, participation in an SLM project, and the quantity of fertilizer used are positively significant. So, older farmers who use a large quantity of input (herbicide, labor, NPK fertilizer, and urea), who are in the North Cotton Zone (ZCN), and who participated in an SLM project have a higher yield than non-adopters. The negative significance of the interaction term for gender and the amount of fertilizer used suggests that the impact of CM adoption on maize yield is lower among female producers and producers who use little fertilizer. For the model of the impact of PP adoption on maize yield, the coefficients of age, amount of NPK, type of seed, and participation in an SLM project are positively significant, suggesting that older producers, who use a large amount of NPK, traditional seed and have participated in an SLM project tend to achieve a higher yield. But the negative coefficient observed for the quantity of labor indicates that these farmers obtain a lower maize yield with higher labor use. As for the CR impact model on maize yield, the coefficients of age, the quantity of herbicide, the quantity of NPK, participation in an SLM project, and the quantity of fertilizer used are positively significant. This suggests that older farmers who use a great quantity of herbicide and NPK and have once participated in an SLM project have higher maize yields. The coefficient of sex variable is negative and significant, suggesting that female farmers who adopt CR have a higher maize yield than males. For MP, the coefficients of the quantity of urea and participation in an SLM project are positively significant. It implies farmers who have adopted MP and participated in an SLM project have higher maize yields. The negative co-

Table 2: Estimated local mean exponential response function (LARF) coefficients for yield

Log yield	CM	PP	CR	MP
SLM	0.225 (0.161) ***	0.085 (0.203) ***	0.128 (0.469) ***	0.027 (0.696) **
Age	0.115 (0.129) **	0.146 (0.134) **	0.025 (0.033) *	-0.170 (0.137)
Gender	0.075 (0.068) *	0.064 (0.067)	-0.055 (0.067) **	0.068 (0.068)
Herbicide quantity	0.013 (0.009) **	0.009 (0.009)	0.007 (0.008) *	0.013 (0.010)
Labor quantity	0.009 (0.027) ***	-0.059 (0.027) **	0.028 (0.022)	-0.011 (0.027) ***
NPK quantity	0.009 (0.028) **	0.007 (0.027) ***	0.010 (0.027) **	0.001 (0.029)
Quantity of Urea	0.042 (0.025) **	0.036 (0.023)	0.034 (0.025)	0.043 (0.025) *
Type of seed	0.093 (0.103)	0.054 (0.114) **	-0.128 (0.121)	-0.088 (0.121)
Soil fertility level	0.093 (0.059)	-0.089 (0.059)	-0.045 (0.057)	-0.088 (0.061)
Production area	0.135 (0.123) **	0.131 (0.131)	0.190 (0.132)	0.209 (0.136)
Participation in an SLM project	0.163 (0.071) **	0.125 (0.069) **	0.115 (0.067) *	0.138 (0.074) **
Quantity of fertilizer used	0.107 (0.065) *	0.110 (0.064) *	0.112(0.065) *	0.106(0.065)
Gender # SLM	-0.068 (0.028) **	0.072 (0.081)	0.051(0.030) **	0.065(0.048) ***
Quantity of fertilizer # SLM	-0.103(0.050) *	0.087 (0.072)	0.126 (0.040) **	0.109(0.022) **
Wald test (Ho: all the coefficients of the interactions=0)	13.92***	10.02***	56.09***	32.98***
Adjusted R^2	0.411	0.316	0.384	0.411
Number of respondents	289	278	322	264
Impact estimators				
LATE WALD	0.17 (0.94) ***	0.063 (18.14) **	0.120 (0,19) ***	0.056 (0,15) **
LATE LARF	0.209(0.197) **	0.087(0.279) ***	0.128(0.469) ***	0.027(0.696) **

*Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.*

efficient observed for the quantity of labor indicates that farmers who have adopted MP obtain a lower maize yield with higher labor use. Also, the positive significance of the interaction terms for sex and quantity of fertilizer used in the adoption of CR, PP, and MP shows that their impact is higher for males and those who use little fertilizer.

Impact of the adoption of SLMTs on labor Productivity (LP) and its determinants

The impact of SLMTs adoption on labor productivity was estimated and presented in Table 3. The estimation results show that the adoption of SLMTs positively impacts maize farmers' LP of maize farmers. CM, PP, CR, and MP adoption increases LP by 40.7%, 37.9%, 53.1%, and 41.3%, respectively. We also estimated the determinants of the adoption of SLMTs on LP of maize farmers. These variables include the farmers' age, gender, education, inputs price, the type of seed, and level of soil fertility. Concerning the CM model, the coefficients of age and the level of soil fertility are positive and significant. This indicates that farmers who are older and produce on fertile soils have high LP. The coefficients of gender and the price of the inputs (herbicide, NPK, and urea) are negative and significant, suggesting that women have a higher LP than men. Those who use CM tend to get a lower LP when the input price increases. For the PP model, the coefficients of education and level of soil fertility are positive and significant. This indicates that educated farmers producing on fertile land have high LP. The coefficients of age and price of inputs (herbicide, NPK, and urea) are negative and significant, suggesting that the young farmers who adopted PP have a higher LP. Also, when the price of inputs increases, LP decreases. Concerning MP, the coefficients of age and NPK price are negative and significant. This indicates that younger farmers achieve higher LP than older. Moreover, when NPK fertilizer price increases, LP decreases. The opposite effect is true with the price of Urea ceteris paribus. The study also shows that the urea price is positively associated with LP when farmers apply CR. However, the type of seed used is negatively associated with LP for those farmers. It implies that adopting CR and using traditional seeds improve LP. It is worth to note the positive coefficient of the interaction term between gender and the adoption of CM indicates that men who adopted CM have higher LP compared to women

Impact of the Adoption of SLMTs on Profit and its Determinants

Table 4 presents the results of the impact of SLMTs adoption on farmers' maize profit. The results show that SLMTs adoption impacts maize farmers' profits. LATE estimation show that the adoption of CM, PP, CR, and MP significantly increases maize profit by 15%, 6.9%, 11.4%, and 7%, respectively. These proportions correspond to the average variations in maize profit due to the causal effect of adopting SLMTs. Table 4 also presents the determinants of maize profit from the LARF. Apart from a change in SLMTs, other social and economic variables significantly explain the variation observed on profit. These variables include age, gender, education, price of inputs (herbicide, NPK, Urea), type of seed, use of chemical fertilizer, level of soil fertility, production area, and the quantity of fertilizer used. The interaction terms are statistically significant, thus confirming the heterogeneity of the impact of SLMTs adoption on the profit of maize farmers. The F-statistics of the four impact models for the joint significance of the interactive terms indicate that they are statistically significant and different from zero.

Table 3: Estimated local average exponential response function (LARF) coefficients for Labor Productivity

Log labor productivity	CM	PP	CR	MP
SLM	0.407(0.792) **	0.379(0.018) ***	0.531(0.007) ***	0.413(0.318) ***
Age	0.256(0.631) **	-0.109(0.671) *	-0.066(0.166)	-0.188(0.677) *
Gender	-0.397(0.333) *	-0.419(0.335	-0.526(0.335)	-0.373(0.338)
Education	0.036(0.047)	0.045(0.049) *	0.031(0.044)	0.034(0.051)
Herbicide price	-0.012(0.133) **	-0.106(0.135) *	0.005(0.110)	0.037(0.137)
NPK Price	-0.265(0.138) **	-0.275(0.136) **	-0.223(0.135)	-0.271(0.143) **
Urea price	-0.302(0.124) **	-0.258(0.118) **	0.240(0.123) **	0.305(0.127) ***
Type of seed	-0.761(0.507)	0.927(0.572)	-0.041(0.603) *	-0.975(0.599)
Use of chemical fertilizer	0.290(0.290)	-0.424(0.298)	-0.301(0.282)	-0.364(0.304)
Soil fertility level	0.036(0.602) **	0.331(0.656) ***	-0.0137(0.658)	0.037(0.674)
Production area	0.279(0.348)	0.050(0.345)	0.239(0.335)	0.218(0.366)
Quantity of fertilizer used	0.035(0.318)	0.015(0.322)	0.106(0.325)	0.084(0.325)
Gender # GDT	0.365(0.633) *	0.461(0.391)	0.565(0.001)	0. 301(0.303)
Quantity of fertilizer # GDT	0.328(0.811)	0.005(0.008)	0.459(1.677)	0.002(0.369)
Wald test (Ho: all the coefficients of the interactions=0)	21.89**	42.13***	52.18***	11.89***
Adjusted R^2	0.369	0.468	0.37	0.370
Number of respondents	289	278	322	264
Impact estimators				
LATE WALD	0.256 (0,15) **	0.256 (0,15) **	0.256 (0,23) **	0.367 (0.17) *
LATE (LARF)	0.407(0.792) **	0.379(0.018) ***	0.531(0.007) ***	0.413(0.318) ***

*Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.*

At the level of the CM adoption impact model on profit, the coefficients of gender, education, type of seed, and quantity of fertilizer used are positively significant. This indicates that being a man and educated increases your profit. The same observation is made with farmers who use a large quantity of fertilizer and conventional seed. However, the production zone negatively impacts farmers' profit. Being in the northern cotton zone and using CM have lower maize profits than those who do not use them. In the model of PP, the coefficients of age, education, type of seed, and quantity of fertilizer used are positively significant. It shows that older farmers use traditional seeds and more fertilizer while those educated have higher profits than non-adopters. The coefficients of Urea price and NPK are negative, indicating that farmers' profit decreases when the prices of these inputs increase. According to CR model, the coefficients of seed type, fertilizer use, and quantity of fertilizer used are positive. This implies that the farmers who use conventional seeds with a large quantity of fertilizer have higher profit. On the other hand, the coefficients for age, gender, and herbicide price are negative. This result shows that young farmers, especially women, tend to have lower profits when the price of herbicide increases. In the case of MP adoption impact on profit, the coefficients of age, education, seed type, and production area are significant. This suggests that older, educated farmers based in the northern cotton zone using traditional seeds who adopted MP have higher profits than non-adopters.

It is worth highlighting the negative coefficients of the interaction terms between gender and the adoption of PP, MP, and CM. This interaction indicates that women who adopted PP, MP, and CM have lower profits than men. However, men who have adopted CR have higher profits than women. Also, farmers who have adopted CR in combination with a large quantity of fertilizer obtain higher profits than those who have adopted Mucuna.

DISCUSSION

In light of the different results, SLMTs adoption positively impact maize yield, LP, and profit of maize farmers. These findings are consistent with recent impact studies that revealed that SLMTs adoption improves farmers' maize yield, profit, and LP (Abdulai and Huffman, 2014; Adolwa *et al.*, 2019; Martey *et al.*, 2019, 2021). The results also indicate that women obtained the best profits compared to men. This is due to the adequate allocation of productive resources at the level of women and the fact that they have relatively small plots of land, which allows them to make optimal use of inputs. Profit is influenced by maize yields and many other factors like sales price of production, which can lead to insignificant or significant results.

The significance of the soil fertility level variable reveals the importance of environmental variables to estimate profit and LP to avoid biased estimates. These results corroborate those of Abdulai and Huffman (2014), who showed that the percentage of land perceived as fertile impacts land productivity in water and soil conservation technologies adoption. Others studies showed that perception on land degradation is a key factor on the adoption of SLMTs (Abukari and Abukari, 2020; Ndagijimana *et al.*, 2019). The results from the profit model showed the positive influence of the use of mineral fertilizer. Indeed, the organic matter restored by the SLMTs adopted makes it possible to have a positive response from mineral fertilizers. Indeed, organic matter allows the soil to maintain moisture by protecting it from the sun's rays. The combined effect of the SLMT studied and the inorganic fertilizer increases the profit of men who have adopted PP and CR. This may be due to the increase in yield. These results are the opposite of those found by Hörner and Wollni (2022), who highlighted that this combination is not fully reflected in the value of crops. Our results also showed the positive effect of improved seeds on the model of maize yield and profit and the negative effect on LP.

Table 4: Estimated coefficients of the local mean exponential response function (LARF) for profit

Log profit	CM	PP	CR	MP
Age	0.156(0.080)	0.229(0.132) *	-0.159(0.280) ***	0.457(0.249) **
Gender	0.016(0.570) **	0.024(0.566)	-0.056(0.565) **	0.031(0.026) *
Education	0.071(0.081) *	0.080(0.083) **	0.045(0.074)	0.081(0.577) ***
Herbicide price	-0.037(0.228) ***	-0.196(0.228)***	-0.071(0.186) **	-0.014(0.088) *
NPK Price	-0.318(0.236) *	-0.399(0.229) **	-0.264(0.228)	-0.518(0.233)
Urea price	-0.290(0.213) *	-0.215(0.199)	0.210(0.209)	0.433(0.245)
Type of seed	0.644(0.868) **	0.688(0.964) **	0.811(0.018) **	0.900(0.218) ***
Use of chemical fertilizer	0.621(0.496)	0.766(0.502) ***	0.344(0.476) **	-0.667(0.023)
Soil fertility level	0.648(0.029)	0.581(0.106)	0.071(0.110) *	0.202(10.150)
Production area	-0.495(0.596) *	0.008(0.582)	0.183(0.566)	0.400(0.624) **
Quantity of fertilizer used	0.877(0.544) **	0.027(0.543) *	0.895(0.549) *	0.844(0.555)
Gender # GDT	-0.015(0.012)***	-0.024(0.35) **	0.056 (0.571) **	-0.031(0.024) **
Quantity of fertilizer # GDT	0.812(0.498)	0.029(0.633)	0.731(0.355) ***	-0.851(0.255)***
Wald test (Ho: all the coefficients of the interactions=0)	0,20***	30,81***	90,34***	40,07***
Adjusted R^2	0.701	0.622	0.381	0.713
Number of respondents	289	278	322	264
Impact estimators				
LATE WALD	0.111 (7.12) **	0.023 (0.027) ***	0.067 (0.17)	0.031(0.358) **
LATE LARF	0.150(0.377) *	0.069(.457) ***	0.114(0.255) ***	0.07(0.57) ***

Significant at the 10% level; ** Significant at the 5% level; * Significant at the 1% level.*

As already observed from the descriptive statistics, the level of improved seeds use in rural areas is low. Improved seeds increase the productive potential of these restored soils rich in organic matter. Our results are consistent with those of Di Falco and Veronesi (2013), who found that changing crop varieties positively impact net incomes when combined with crop water and soil conservation strategies, but not when implemented in isolation.

The negative sign observed of CR on LP is related to farmers' misinterpretation of some seed. The results in Tables 3 and 4 indicate that education is a key factor explaining the higher profits and LP of maize among SLMTs adopters. This indicates that good knowledge and understanding of PP can improve farmers' profits. Mastering PP, CM, and MP usage improve LP. These results are consistent with the findings of recent related SLMT studies (Abdulai and Huffman, 2014; Adjiba *et al.*, 2021; Mango *et al.*, 2017). SLMTs increase labor demand through additional technology-related activities. As revealed by the descriptive statistics, SLMTs adopters used more labor than non-adopters. Thus, the application of SLMTs induces additional costs in labor and the cost. This could be a constraint or a major barrier to the SLMTs adoption. These results are in line with the conclusions of Etongo *et al.* (2018). The coefficients of the fertilizer application variables (NPK and Urea) and herbicide in Table 2 are positive and statistically significant. This implies that farmers who use more mineral fertilizers and more inputs achieve higher maize yields. On other words, the use of more inputs leads the farmers to an intensive agricultural practice on small areas. These results corroborate those of Abdulai and Huffman (2014). On the other hand, the coefficients of the price of NPK and urea fertilizers and that of the herbicide in Tables 3 and 4 all have expected and significant negative signs for some SLMTs. This indicates that if input prices increase, profits, and LP decrease. These results support the conclusions of Abdulai and Huffman (2014). The results in Table 2 show that the coefficient of participation in a soil fertility restoration project is positive on yield. Farmers improve their knowledge from these projects on how to apply SLMTs. These results are in line with those of Martey *et al.* (2021), who showed that participation in agricultural development projects strengthens the capacities of farmers. We have also noticed a heterogeneity of the impacts according to farmers' location. According to Adolwa *et al.* (2019), farmers did not experience the same impact as the two targeted areas in their study area. Our results confirm recent SLMT-related studies (Abdulai and Huffman, 2014; Hörner and Wollni, 2022; Martey *et al.*, 2019). Age, as well as gender, showed ambiguous signs of the impact of SLMTs adoption. Older men achieved the best yield. On the other hand, the influence of age is ambiguous on profit and LP concerning the technologies studied. Indeed, agricultural experience comes with age. This result explained that age was statistically significant and positive in explaining variations in profit of adopters of PP and MP technologies. An older farmer with rich experience who adopts SLMTs is likely to generate more income (Oduniyi and Tekana, 2021). Only the association of age with profits on CR adopters is different.

CONCLUSION

In this article, we used data collected from farmers to examine the factors and impacts of SLMTs adoption on yields, profits, and labor productivity among maize farmers in North East of Benin. The results indicated significant differences between men and women. However, knowing the differences between the means of variable of interest is not sufficient to understand adoption decisions in a sample of farmers, as these do not account for the impact of other farmer characteristics. To account for endogeneity and selectivity biases and capture the differential impact of adoption on adopters and non-adopters of the SLMTs we used the LATE model. These results indicated a positive and significant impact of education on profit and labor productivity for some SLMTs. This reveals the importance of education in rural areas for productivity gains. The use of herbicides increased yields for some SLMTs. This shows that it is important to consider this aspect when introducing SLMTs. However, herbicide prices have a negative impact on farmers' profits. These prices also have a negative impact on the labor productivity due to the introduction of certain technologies. The application of mineral fertilizers (NPK and urea) has a positive and significant impact on the yield.

It is also important to consider geographic heterogeneity when analyzing the impact of SLMTs adoption. The results indicated for example that the North Cotton Zone has a comparative advantage over the other zones. Our results also confirmed the importance of farmers' perception of land quality in deciding which technologies they would use and the potential impact this could have on yield, profit, and labor productivity. Therefore, differences in soil conditions, among other social and economic factors, must also be considered to accurately explain the introduction and impact patterns of SLMTs adoption in Benin, particularly in sub-Saharan Africa.

LATE estimation suggested that CM, PP, CR, and MP adoption increases yield by 20.9%, 8.7%, 12.8%, and 2.7%, respectively. The increase in labor productivity of adopters is 40.7%, 37.9%, 53.1%, and 41.3% for CM, PP, CR, and MP, respectively. At the profit level, the causal impact of adoption is 15%, 6.9%, 11.4%, and 7%, respectively for CM, PP, CR, and MP.

Overall, our results have policy implications for SLMTs diffusion to enhance agricultural productivity. In particular, they suggest that effective policies to encourage the adoption of new technologies should include improving farmers' training systems and providing incentive mechanisms for using improved seed on restored soils for higher productivity gains. To ensure the effective dissemination and SLMTs adoption, the government should subsidize chemical fertilizers and consider making them available to maize farmers. Researchers should also try to formulate recommended dosages of mineral fertilizers in addition to SLMTs adoption, which will not only help restore the state of organic matter but also provide seedlings with essential nutrients (N, P, K). This is a prospect for future research for soil scientists. It is also necessary to target women in particular, since these technologies allow them to increase their income. This is a way to reduce poverty in rural areas in developing countries.

Finally, we urge future research to look beyond crop yield when investigating SLMTs adoption. The results showed that yield is not an indicator of economic viability. Outcomes indicators like profit and labor productivity are more important for leading farmers to make decisions. The main limitation of this study is that the impact of combining these technologies on outcome indicators has not been studied and future research could investigate that.

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