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Adoption and Impact of the Improved Fallow Technique on Cotton Productivity and Income in Zambia

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Abstract

An improved fallow is a soil fertility agroforestry technique that has commonly been used in the staple maize production systems of Zambia and sub-Saharan Africa. Several studies have assessed the adoption and impact of the improved fallow on maize production. Generally, it has been observed that though the improved fallow does increase maize yields, its efficacy on welfare in terms of increased income is low. The use of the technique on cash crops that could significantly contribute to household welfare has rarely been investigated. This study assessed the factors affecting the adoption and impact of improved fallows on a commonly grown cash crop, cotton, in the cotton growing provinces of Zambia. The study used a sub sample (N=1206) of the nationally representative 2014/15 Rural Agricultural Livelihoods Survey (RALS) data which was randomly collected by the Indaba Agricultural Policy Research Institute (IAPRI) and Central Statistical Office (CSO) of Zambia. The determinants of improved fallow adoption among the cotton farmers were examined through the use of the probit model while the impact of the technique on cotton production and income was evaluated by using the propensity score matching and the endogenous switching regression models. Among the socioeconomic factors significantly increasing the probability of improved fallow adoption included: increases in age, education level, and per capita productive assets of the farmer, in addition to the area under cotton production and the distance of the homestead to the market. Institutional factors found to increase the farmer's likelihood of adopting the improved fallow in the cotton production systems included; farmer membership to a cooperative, receiving improved fallow seedlings from the government projects and having information on agroforestry tree species. On the other hand, an increase in land size per capita was found to negatively affect the likelihood of improved tree fallow adoption. Impact estimates showed significant cotton yield and income increases as a result of adopting the technique. The continuous provision of information on relatively new techniques such as the improved fallows preferably in farmer organized groups, and support towards the provision of the technique's planting materials are some of the areas requiring government and NGOs attention. In addition, the study recommends that the farmers' formal education level should be enhanced and that improved tree fallows should also be explicitly promoted on cash crops that have similar agronomic requirements to maize such as cotton.

Keyword: improved tree fallows, adoption, probit model, propensity score matching, endogenous switching regression model, Zambia

1. Introduction and Background

Deforestation and land degradation are some of Zambia's key environmental issues (Vinya *et al.,* 2011). Deforestation rates are significant in Zambia, with approximately 300,000 ha of forest cover lost per year (Day *et al*., 2014). Apart from wildlife reduction, loss of biodiversity and ecosystem lost value, land degradation is one of the key environmental problems in Zambia that is linked to rampant deforestation (Slunge, 2010). This problem constrains poor households' income opportunities through lowering agricultural productivity and access to various non-timber products (Slunge, 2010). Agroforestry systems of soil improvement can be an efficient strategy to ease the problem of land degradation and nutrient depletion and therefore address food security issues by potentially improving crop productivity, sustaining crop yield increases, diversifying smallholder farmers' income and protecting the environment (Leakey, 2010). Agroforestry systems in the form of improved tree fallows also commonly referred to as fertilizer tree fallows can help farmers improve their yield in addition to improving the microbiological, chemical and physical conditions of the soil. In most cases, the fallows can also control weeds and are a source of useful by-products such as firewood and medicine (Ajayi *et al*., 2005).

The improved tree fallow technique is an ecologically robust approach to soil fertility improvement that is composed of fast growing, mostly nitrogen fixing, trees of *Faidherbia albidia, Sesbania sesban, Gliricidia sepium, Tephrosia vogelii* and *Cajanus cajan*, that guarantees the shortest soil restoration period of 2–3 years. Thereafter, farmers can grow their crop on formerly improved fallow plots for the next 3–4 years minus applying any fertilizer. Agroforestry technologies are cheaper and do not require any direct cash expenses associated with mineral fertilizers (Ajayi, 2007). However, unless farmers widely adopt these technologies as part of their farming system, the potential benefits of agroforestry on livelihoods and the environment will not be realized. Despite positive results from on-station and field controlled experiments, the farmer uptake of the improved tree fallow technologies in Zambia has been generally dismal (Kuntashula and Mungatana, 2014).

In Zambia, most research and evaluation studies (Ajayi, 2003; Franzel, 2004; Kuntashula and Mungatana, 2014) on adoption and impact of improved tree fallows have concentrated on the staple maize yields and associated income. The use of improved tree fallows and impact thereof on cash crops other than maize such as cotton which has similar nutrient demands as maize has rarely been investigated. Rigorous literature search show that the experimentation and promotion of the technology has largely focused on maize as a beneficiary crop for nutrients fixed by the fallows. As maize grown mainly for subsistence requirements, the impact estimates of the technique on outcomes such as household income could be underestimated. Moreover, if farmers observe relatively small impacts due to the use of the technique on a crop that does not produce significant cash outlay, the adoptability potential could be low. Will the impact of the technology on cash crops be more pronounced, and hence encourage adoption? Thus, the main objective of this study was to determine the impact of improved tree fallows on cotton production which is solely grown as a cash crop in selected cotton producing areas of Zambia, and to identify the determinants of this adoption. This study contributes to literature on improved fallow adoption and impact estimation in two ways. First, as far as our literature search is concerned, this is the only study in Zambia that has assessed adoption of improved tree fallows on a cash crop such as cotton. Secondly, to ensure high quality impact estimates that account for endogeneity bias, only matched samples of adopters and non-adopters are subjected to the robust endogenous switching regression impact estimation. Results show that factors such as membership to a cooperative, receiving improved tree fallow seedlings from the government projects and having information on agroforestry tree species as well as farmer characteristics such as increased age of the household head, education level of the household head, productive assets per capita and area of cotton field have an effect on adoption of the technique in cotton production. Impact estimates proved the technique’s efficacy in increasing both cotton yields and income from the crop.

2. Materials and Methods

2.1 Data and Data Sources

The study used a sub sample (N=1206) of the nationally representative 2014/15 Rural Agricultural Livelihoods Survey (RALS) data which was randomly collected by the Indaba Agricultural Policy Research Institute (IAPRI) and Central Statistical Office (CSO) of Zambia in collaboration with the Central Statistical Office (CSO) and the Ministry of Agriculture (MA) between June and July 2015. For the nationally representative sample, CSO draws the sample from all the districts in Zambia. For sampling purposes, the CSO subdivides each administrative division of a district into Census Supervisory Areas (CSA) and Standard Enumeration Areas (SEAs). Each SEA contains between 100 – 150 households. A total sample of 680 CSAs is allocated nationally to each Province and district proportional to its size in terms of households. About 20 households are randomly selected from each of the 680 SEAs in the sample (RALS12 Sampling Manual).

Recognizing the fact that not all regions are dominant cotton producing areas in Zambia, we imposed an inclusion condition that the households to be included in our sub sample for analysis should be those coming from the major cotton producing areas. With this requirement, this study used a sub sample of 1, 206 households (out of RALS15 sample of 7934) from Central, Eastern, Muchinga and Southern, provinces which were found to be the major cotton growing provinces in Zambia.

2.2 Conceptualizing Factors Influencing on Adoption and Impact of Improved Fallows in Cotton Producing Areas

2.2.1 Farmer and Household Characteristics

Studies by Ajayi *et al.* (2003), Ajayi *et al.* (2006), Gladwin *et al.* (2002) and Kuntashula *et al.* (2004) showed that the variables: age, availability of information about the technology, the technology perceived relative advantage and usefulness, land or farm size and tenure influence the farmer’s adoption of agroforestry in general, and improved fallows in particular. Other factors which increase the probability of adoption of improved fallows among farmers include the level of formal education and level of environmental awareness (Kwesiga *et al.,* 2003). In a review of gender studies and agricultural productivity in Sub-Saharan Africa (Quisumbing, 1996; Thapa, 2009; Peterman *et al.,* 2010; and Ragasa *et al.,* 2013), it was shown that male-headed households were more likely to adopt new technologies compared to their female-headed counterparts. Jera & Ajayi (2008) and Kassie *et al.,* (2012) contend that females respond less favorably to new technology as compared to the male headed households, though some female headed households are also enthusiastic enough and would as well be more willing to try new technology.

Some of the limitations affecting adoption of agroforestry technologies such as improved fallows include labour for establishing the trees every year and dependency on late rainfall for trees to become established (Thangata *et al.,* 2008). Further, Kuntashula and Mungatana (2015) showed that farmers with access to large quantities of inorganic fertiliser are less likely to adopt improved fallows. This is because improved fallows and inorganic fertiliser are direct competitors in the provision of soil fertility. A study by Matata *et al.,* (2010), on socio-economic factors influencing adoption of improved fallow practices among smallholder farmers in Western Tanzania found that that lack of awareness on improved tree fallows, unwillingness and lack of inability to wait for two years are the major limiting factors of improved tree fallow adoption.

2.2.2 Market Access and Institutional Factors

A study by Mafongoya *et al.,* (2006) in Zambia on the impact of improved tree fallow technology showed that to make a viable impact, agricultural technology innovations should be

directed to the real needs of farmers in significant locations, through active encouragement of user modification and adaptation of the technology. The study also showed that adoption of the technology by farmers is not a direct association centered wholly on technological characteristics, but is influenced by several factors including institutional and policy factors such as fertilizer subsidies, spatial and geographical factors and household-specific variables. Nyoka *et al.,* (2011) discovered that inadequate availability of seed and seedlings is one of the barriers to adoption of improved fallows. Additionally, according to Namwata *et al.* (2010), extension contact has a significant positive impact on the adoption of agricultural technologies. The role of extension contact in influencing adoption is similarly reported elsewhere (Kwesiga *et al.,*2003; Solomon *et al.,* 2011; Ayinde *et al.,* 2010). The noted studies showed that frequency of contact with extension agents influences technology adoption decisions of farmers. Distance to both input and output markets could also be a significant contributor to adoption of improved fallows (Kuntashula and Mungatana, 2015).

2.2.3 Cultural Factors

Haggblade et al. (2004**)** indicated that while economic considerations and short-term profitability of renewable soil fertility replenishment technologies generally increase the probability of its adoption, economic models alone do not fully explain the farmers’ adoption behavior regarding these technologies. The farmers’ adoption decisions appear to be guided by their household’s level of resource endowments and the prevailing social context such as customs, obligations and beliefs which are highly affected by factors such as farmers’ formal education level, age, and family size. Beliefs which were chosen to affect the farmers’ adoption decisions include belief in witchcraft to become successful and belief in prayer is more important than hard work for success.

2.2.4 Regional Characteristics

Spatial and geographical location of a farmer significantly influences adoption of agricultural technologies (Mafongoya *et al.,* 2006). Regions differ in several biophysical as well as climatic factors thus influencing the performance of some agricultural technologies such as the improved fallows. For instance, Nyanga *et al.,* (2011) and CFU (2007) contend that conservation agriculture (which encompasses improved fallows) cannot do well in certain regions with high rainfall in Zambia.

Factors Hypothesized to Affect Adoption of Improved Fallows

Factors that were hypothesized to influence adoption and hence impact of improved fallows in the key cotton growing areas are shown in Table 1. Among the socioeconomic variables, age of household heads was expected to have either a positively or negative influence on adoption of the improved fallows. Older farmers could have the relevant experience in adopting technologies while equally young farmers could be more enthusiastic to try out new ideas. Gender of the household head is also hypothesized to have an ambiguous effect on adoption of improved fallows in cotton production due to reasons already discussed in the section above. Formal education level of the household head was expected to have a positive influence on adoption of the improved fallows.

Marital status of the household head was hypothesized to having an ambiguous relationship with adoption of improved fallows. It was also expected that full time labour equivalence, area under cotton production, total land size, assets, secure land tenure, quantity of fertiliser use, would all positively influence farmer's decisions to adopt the technology (Table 1).

Among the institutional factors, the following variables were hypothesized to have a significant influence on adoption of improved fallows in cotton producing areas. Access to information on agricultural goods prices was hypothesized to have an ambiguous relationship. Membership to various network groups such as membership to a farmer group, saving group and/or women group was expected to have a positive effect on improved tree fallow adoption just like receiving improved fallow seedlings from the government. Distance to the market or town would negatively influence the farmer's adoption of improved tree fallows while receiving extension message on the technology was expected to increase the probability of adoption.

Cultural factors which were expected to affect the probability of adoption of improved fallows included trust in prayers and trust in witchcraft for success. Both had an ambiguous expectation of the adoptability potential of improved fallows in the major cotton producing areas of Zambia (Table 1).

Table 1. Description of variables used in the probit model

Variable name	**Variable Description**	**Expected impact on Adoption**
Dependent variables		
Adoption of improved tree fallows	Dummy=1 if household adopted,0 otherwise	
Explanatory variables		
Farm household characteristics		
Hgender	(Gender=1 if male headed,0 otherwise)	+/-
Hhsize	Household size	+
Headage	Age of the household head in years	+/-
Headedu	Years of formal education of household head	+
Fte	Labour in full time equivalents	+
Hmstatus	(marital status=1 if single,0 otherwise)	+/-
Ha_harvctn	Area in hectares for cotton field	+
Land tenure	Landtenure(=1 if secured,0 otherwise)	+
assets_pc	Value of productive assets percapita	+
land size _pc	Land holding size percapita	+
Ctnfert	Quantity of inorganic fertiliser applied in kg	+
Market access & institutional factors		
Acessinfpr***i***	Access to agricultural good's prices	+/-
farmer group	Belong to a farmer group	+
Womengroup	Belong to women 's group(=1 if yes,0 o/w)	+
Savinggroup	Belong to a saving group(=1 if yes,0 o/w)	+
seedling_gvt projects	Seedlings from government (=1 if yes,0 o/w)	+
Distmkt	Distance to the market in kilometers	-
info_trees	Advice on improved fallows(=1 if yes,0 o/w)	+
Cultural factors		
Trust_Witch	Trust witchcraft for success(=1 if yes,0 o/w)	+/-
Trust_pray	Trust prayer over hard work for success (=1 if yes,0/w)	+/-
Regional characteristics		
Dcentral	Dummy for central Province	+
Deastern	dummy for eastern Province	+
Dmuchinga	dummy for Muchinga Province	+
Dsouthern	dummy for southern Province	+

2.3 Analytical Frameworks

2.3.1 The Probit Model

The behavioral preference of the cotton farmers to either adopt or not adopt improved tree fallows was analyzed using a discrete choice probit model for binary choice (yes, no) responses referring to adoption and non-adoption, respectively. The probit model is a statistical probability model with two groups in the dependent variable (Liao, 1994). The probit analysis is founded on the cumulative normal probability distribution. The binary dependent variable (Y), takes the values of either one or zero (Aldrich and Nelson, 1984). For instance, in this study, in the case of adoption and non-adoption, the dependent variable took the values of one and zero respectively.

Following Greene (2011), the probit model is generally specified as:

$$pi = pr\left[Yi = 1 \mid X1i, \ldots, Xki; \beta 0, \ldots, \beta k\right] = \Phi\left(\beta 0 + \sum_{k=1}^{K} \beta k Xki\right) = \Phi\beta\left(Xik'\right) \quad (1)$$

where pi is the probability of the outcome while P_r, Y_i $X_{ki}, \beta_0, \beta_k, \Phi$ represents the probability that an observation with particular characteristics will fall into a specific one of the groups, the observed outcome of the binary choice problem ,explanatory variables on i individuals, the constant, regression coefficients (impact of changes in X on the probability) and the cumulative distribution of a standard normal random variable, respectively. In this study, the correlation between a specific explanatory variables and the outcome of the probability was interpreted by means of the marginal effect, which explains the *ceteris paribus* effects of changes in the regressors affecting the outcome. The regression coefficients of the explanatory variables in this analysis were used to indicate the significance and direction of the particular variables towards the farmer’s adoption of improved tree fallows. The marginal effect associated with continuous explanatory variables X_k on the probability $p(Yi = 1 \mid X)$, holding the other variables constant, can be derived as follows (Greene, 2011):

$$\frac{\partial pi}{\partial xki} = \phi\left(x_i{}' \beta\right)\beta k \quad (2)$$

Where ϕ represents the probability density function of a standard normal variable. $\phi\left(X' \beta\right)$ is the density function of the standard normal distribution evaluated at $X' \beta$. And $X' \beta$ is the product of the row vector of selected covariate values, X and the column vector of parameter estimates, β. The marginal effects (Δ) on dummy variables (d) refer to discrete changes in the predicted probabilities and are specified differently as;

$$\Delta = \Phi\left(\overline{x}\beta, d = 1\right) - \Phi\left(\overline{x}\beta, d\right) = 0 \;) \quad (3)$$

where $\overline{X}$ represents the means of all the other variables in the model (Greene, 2011).The statistical package, STATA14 was used to implement the probit algorithm analysis.

2.3.2 Propensity Score Matching

The propensity score matching and the endogenous switching regression were used to estimate the impact of the improved fallows on cotton production. In this context the propensity score is the probability of adopting improved tree fallows conditional on the covariates or observable characteristics of the farmers (Xi). Essentially, the Propensity score matching framework matches observations of adopters and non-adopters based on the predicted propensity of adopting a superior technology (Rosebaum and Rubin 1983; Heckman et al., 1998; Smith and Todd, 2005; Wooldridge, 2005). The impression of propensity score matching (PSM) is to match adopting and non-adopting individual farmers, who based on observables, have a very similar probability of adopting the improved tree fallow techniques. With such matching, the difference in the outcome variable can be attributed to the effects of adoption. In other ways, the propensity score reflects the probability of the cotton farmers adopting improved tree fallows subject to their different observed characteristics. Following Rosenbaum and Rubin (1983) and the propensity score can be expressed as;

$$P(X) = \Pr(Di = 1 \mid X \mid) = E(Di = \mid X) \quad (4)$$

where X is a vector of the covariates that are postulated to affect adoption of improved tree fallows, D_i stands for a dummy variable equal to 1 if cotton farmers adopted the improved tree fallows and equal to 0 otherwise, $E(.)$ is the expectation operator. The average treatment effect on the treated or adopters (ATT) of the technique was then calculated as the mean difference in outcomes (crop yields and income) across the adopters and non-adopters. Letting Y_1 and Y_0 to be the yield or income outcomes of the adopters and non-adopters respectively, and T to be an indicator variable for adoption equal to one and non-adoption equal to zero, ATT requires that:

$$E(Y_1 - Y_0 \setminus T = 1) \tag{5}$$

Where; E is the expectation in the difference in the outcome $(Y_1 - Y_0)$ between receiving treatment or adopting, T =1 and the counter factual outcome if treatment or the technology had not been received, T = 0. Two important assumptions are required for successful estimation of the impact of a technology using the propensity score. The first is the overlap or common support assumption which states that for each value for X, there is a positive probability of being both adopters and non-adopters of the improved fallows. The second one is the conditional independence which simply ensures that there exists a set X of observable covariates such that after controlling for these covariates, the potential outcomes are independent of the treatment status. With the above two conditions, within each cell defined by *X*, technique adoption assignment is random, and the outcome of control households can be used to estimate the counter factual outcome of the adopting households in the case of no treatment (adoption) (Nannicini, 2007). Several models were specified in the analysis till the most comprehensive and robust specification that fulfilled the balancing tests and establishment of the common support region was obtained. To ensure some robustness within the PSM estimation, two matching algorithms were used, nearest neighbor and kernel matching that gave a trade-off between matching superiority and effectiveness of the estimators (Caliendo and Kopeinig, 2008).

2.3.3 Endogenous Switching Regression (ESR)

The endogenous switching regression was used to control for unobservable characteristics that could bias our results. ESR model consist of the selection equation and two continuous regressions that define the behavior of the farmer as he faces the two regimes of adopting or not the technologies. The selection equation in this study was stated as:

$$I_i^* = \beta X_i + \alpha Z_i + \mu_i \quad \text{with} \quad I_i = \begin{cases} 1 & if\ I_i^* > 1 \\ 0 & otherwise \end{cases} \tag{6}$$

Where I_i^* is the unobservable variable for technique adoption and I_i is its observable counterpart which is the dependent variable which equals one, if the farmer has adopted and zero otherwise and α are vectors of parameters while X_i are vectors of exogenous variables also included in output equations 5 and 6. Z_i are non-stochastic vectors of variables that explain only the selection process and have no direct effect on the outcome. These variables also cited as instruments are very significant for identification purposes. μ_i is a random disturbance related with the adoption of the technologies (Maddala and Nelson, 1975). The two outcome regression equations where farmers faced the regimes of adopting or not to adopt were defined as follows:

Regime 1

$$y_{1i} = \beta_1 X_{1i} + \varepsilon_{1i} \qquad \text{if} \qquad I_i = 1 \tag{7}$$

Regime 2

$$y_{2i} = \beta_2 X_{2i} + \varepsilon_{2i} \qquad \text{if} \qquad I_i = 0 \tag{8}$$

Where Y_{ji} are the outcome variables (crop yield or crop income) in the continuous equations; β_1 and β_2 are vectors of parameters; and ε_{1i} and ε_{2i} are random disturbance terms. The selection equation and the outcome regression equations were all together estimated using the full information maximum likelihood (FIML) estimation (Lokshin and Sajaia, 2004). Upon its estimation, the endogenous switching regression model was used to compare the various conditional expected outcomes of the farm households.

3. Results and Discussion

3.1 Socio Economic Characteristics of the Cotton Farmers in the Study

To determine the statistical differences in the sample's social economic characteristics, a two sample T- test was carried out between improved tree fallow adopters and non-adopters. Socio economic characteristics were grouped under four broad categories namely; farm household characteristics, market access and institutional characteristics, cultural factors and regional characteristics as shown in Table 2. In Table 2, there are three major columns showing a description of the total sample, adopters of improved tree fallows and non-adopters. Within these columns are the variable means and their standard deviations for the total sample, improved tree fallow adopters and non-adopters. Estimates showed that 17.2% of the 1206 cotton farmers adopted the improved tree fallows. The significantly different characteristics between the adopters and non-adopters; that is those variables whose t-statics is greater than two included level of formal education of the household head, land size per capita, total land holding size, cotton yield, total cultivated land, tropical livestock units, receiving seedlings from the government, distance to the market and receiving advice on improved fallows. In terms of the location of the farmers in this study, it was found that 5%, 71%,14% and 11% of the adopters were located in Central, Eastern, Muchinga and Southern Province respectively. On the other hand, 11%,72%,10%, and 7.2% of the non-adopters were located in Central, Eastern, Muchinga and Southern Province respectively. The average land size per capita in the whole sample was about 0.73 hectares, with 0.53 hectares for adopters and 0.78 hectares for non-adopters. The average quantity of fertiliser applied by the farmers in the whole sample was 162.04kg while 106.48 kg and 174.11kg was applied by adopters and non-adopters respectively.

The average land holding size of the household head was 4.2 hectares, with 2.93 hectares for adopters and 4.48 hectares for non-adopters correspondingly. Non-adopters had large hectares which might have in the first place made it difficult to plant and manage large hectares of improved fallows. The average cotton yield for the whole sample was 1078kg/ha and the average cotton yield for adopters and non-adopters was 1290.5kg/hand 1035kg/ha respectively. The average total cultivated land for the total sample was 3.0 ha while the adopters average total cultivated land was 2.44 ha and the non-adopters total cultivated land was 3.07 ha. The non-adopters had significantly higher livestock holding than the adopters suggesting that cotton farmers that have more livestock are generally less likely to adopt improved fallows. The reason may be that livestock are devoted to provide labour for conventional practices such as ploughing. However, this finding does not agree with results from studies done by Kassie *et al.* (2012), Phiri *et al.* (2004) and Keil *et al.* (2005). About 4% of the total sample received improved tree fallow seedlings from the Government while approximately 10% of the adopters and 0.2% of the non-adopters received improved fallow seedlings from the Government.

The average distance to the market for the whole sample was 46.0 kilometres while the adopters and non-adopter's average distance to the was 57.72 kilometres and 44.2 kilometres respectively. About 44% of household heads in the whole sample received advice on improved fallows. On average, 60 % of the adopters received advice on improved fallows while 41% of the non-adopters received advice on improved fallows. This finding that availability of information on the technology and extension services have a positive impact on the farmer's adoption of technology has been acknowledged and documented in many studies such as Solomon et al., (2011), Ayinde *et al.,* (2010), Namwata et al., (2010), Odoemenem and Obinne (2010), Matata *et al.*, (2010), Kwesiga *et al.,* (2002) Boahene *et al.,* (1999), and Omoregbee (1998).

The whole sample 's average cultivated area for cotton was about 0.93 hectares. Meanwhile, the adopters' average cultivated area for cotton was 0.90 hectares and the non-adopters average cultivated area for cotton was 0.93 hectares. Non-adopters had larger hectares of cultivated area for cotton which might have in the first place made it seemingly difficult for them to plant and manage larger hectares of improved fallows. Cotton yield was statistically higher for adopters than non-adopters. This result is similar to the findings of Kuntashula and Mungatana (2013), Quinion *et al.,* (2010), Ajayi *et al.*, 2009, Ajayi *et al.*, (2007), Franzel (2004), and Place *et al.*, (2002) which show that improved fallows increase crop yields though not necessarily cotton. These studies originally contributed to the reason why this study was carried out because no study had evaluated the efficacy of improved fallows on cotton yields**.**

Overall, the average household size of the whole sample, for adopters and non-adopters was about 6 people. A look at education levels shows that on average household heads had about 6 years of formal education. The adopters and non-adopter's household head's average number of years of formal education were 6 years and 5 years respectively. The fulltime equivalence for the whole sample was about 6 workers. In terms of marital status, about 3% of the households in the whole sample were single while 3% of the adopters and 3 % non-adopters were also single. The average age of the household heads in the whole sample was 46.0 years while the adopters and non-adopter's average ages were 45 years and 46 years respectively as shown in Table 2. In terms of the gender of the household head, about 85 % of the total sample were male headed.

About 2.0 % of the whole sample, for both adopters and non-adopters had a land tenure. The average value of productive assets per capita was about ZMW 2,730 for the whole sample and ZMW 2460 for non-adopters and ZMW 2,800 for adopters. The average value of cotton sales at the actual price was ZMW 2501.8 for the whole sample, ZMW 2986 for adopters, and ZMW 2401 for non-adopters respectively. On average about 1% of the total sample had access to information on agricultural good's prices. Other socio economic characteristics which were included in this study were membership to a farmer group, membership to a saving group, membership to women group, belief in prayer than hard work for success, belief in witchcraft to become successful and the location of the farmer (regional characteristics). Despite statistical insignificances in some variables, nearly all variables had similar mean values as seen in Table 2. Therefore, it is obvious that both groups were comparable in their characteristics. This observation inspired the need to approximate the impact of improved fallows in a more robust way.

Table 2. Descriptive statistics of the study sample

	Whole sample		**Adopters**		**Non-adopters**	
Variable name	**Mean**	**Std dev**	**Mean**	**Std dev**	**Mean**	**Std dev**
Farm household characteristics						
Household size	6.2	0.76	6.07	2.4	6.34	2.2
Labour in Full time equivalents	6.08	2.57	5.9	2.35	6.12	2.61
Years of formal education of household head	5.6	0.1	6.5	0.23	5.4*	0.11
Marital status(=1 if single)	0.03	0.01	0.03	0.01	0.03	0.01
Gender of hh head(=1 if male)	0.85	0.36	0.85	0.36	0.85	0.36
Age of the household head in years	46.0.	0.4	45.1	0.88	46.2	0.43
Cultivated area for cotton (ha)	0.93	0.84	0.90	0.84	0.93	0.84
Land size (ha) per capita	0.73	0.03	0.53	0.5	0.78*	1.06
Quantity of fertiliser applied (kg)	162.04	29.16	106.48	37.42	174.11	34.32
Total Landholding size(ha)	4.2	5.6	2.93	2.3	4.48*	6.0
Land tenure(=1 if secure)	0.02	0.01	0.02	0.34	0.02	0.38
Productive assets value per capita(ZMW,000)	2.73	6.42	2.46	4.4	2.8	6.8
Cotton Yield(kg/ha)	1078	681	1290.5	50.96	1035*	20.92
Total cultivated land in ha	3.0	0.07	2.44	0.13	3.07*	0.08
Value of cotton sales at actual price(ZMW)	2501.8	2219.3	2986	2178	2401	2216
Livestock holding(Tropical Livestock units)	5	11.38	3.24	0.38	5.22*	0.5
Total net off farm income(ZMW)	3636.3	9537.8	3407.9	7483	3684	9915.1
Market access and Institutional factors						
Price infor access(=1 if yes)	0.01	0.4	0.01	0.36	0.01	0.4
Farmer group member(=1 if yes)	0.02	0.5	1.5	0.5	0.02	0.5
Women group member(=1 if yes)	0.02	0.42	0.02	0.41	0.02	0.42
Saving group member(=1 if yes)	1.93	0.01	1.91	0.02	1.94	0.01
Seedlings from government(=1 if yes)	0.04	0.19	0.1	0.3	0.002*	0.05
Distance to the market in Km	46.0	1.1	57.72	46.4	44.2*	33.8
Advice on improved fallows(=1 if yes)	0.44	0.5	0.6	0.5	0.41*	0.5
Cultural Factors						
Belief in witchcraft for success	0.03	0.4	0.03	0.01	0.03	0.01
Trust prayer over hard work for success	0.03	0.02	0.03	0.01	0.03	0.02
Regional characteristics						
Dcentral	0.11	0.3	0.05	0.21	0.11	0.3
Deastern	0.72	0.45	0.71	0.46	0.72	0.5
Dmuchinga	0.1	0.31	0.14	0.4	0.1	0.3
Dsouthern	0.08	0.27	0.11	0.31	0.072	0.26
No. of observations	**1206**		**208**		**998**	

*Significant differences between adopters and non-adopter's means

Source: Author's own calculation-RALS 2015

Note: A TLU (Tropical Livestock Unit) is an animal unit that refers to an animal of 250kg live weight, and is used to aggregate diverse species and classes of livestock as follows: Bullock:1.25; cattle 1.0, goat, sheep and pig:0.1; guinea fowl, chicken and duck:0.04 and turkey:0.05. (Compiled after janke 1982)

3.2 Factors Affecting the Adoption of Improved Fallows among Cotton Farmers in Zambia

Estimates on factors affecting the adoption of improved tree fallows in cotton production using the probit regression are shown in Table 3. Among the significant factors that positively influenced the farmers' adoption of improved fallows included: the age of the household head, education level of the household head, area under cotton production, value of productive assets per capita, distance to the market in kilometers, receiving improved tree fallow seedlings from the government, receiving advice on improved fallows and the farmer's location. Landholding size per capita negatively influenced adoption of the improved fallows among the cotton farmers.

An increase in the age of the household head by one year was found to increase the probability of improved fallow adoption by 4.4%. It could be speculated that the older the people become, the wiser they could become in trying out productive and sustainable technologies not only in the production of staple foods but cash crops such as cotton as well. An increase in education level by one year would increase the probability of improved fallow adoption by 3.2%. Improved fallow has generally been touted as being a knowledge intensive technology. Therefore, farmers who are more educated are likely to adopt the technology.

Other studies (Matata *et al.*, 2010; Kwesiga *et al.*, 2003) have also shown a positive relationship between education and adoption of technologies. An increase in cultivated area for cotton by one hectare increases the farmer's probability of improved fallow adoption by 9.9%. This finding could imply that the adopters of improved fallows in the cotton producing areas are doing so out of a need to have maximum soil fertility improving benefits in the production of cotton. When the household's value of productive assets per capita increases by one thousand Zambian Kwacha, the probability of improved fallow adoption increases by 1%. Generally, productive assets can contribute to increasing the farmers' opportunities to be engaged in a wide range of farming enterprises. For example, farmers that own oxen are capable of cultivating larger pieces of land within a short time or they would hire out oxen for extra resources to pay for labour or purchase other inputs. Therefore, farmers who own productive assets are likely to try out new technologies such as the uptake of improved fallows. Earlier studies by other authors such as Keil *et al.*, (2005) and Phiri *et al.*, (2004) postulated a similar relationship. An increase in distance to the market increases the probability of adoption of improved tree fallows by 0.4%. It appears like farmers in the remotest areas are more likely to take up the technology than those near trading centers. This could probably be attributable to reduced soil fertility options among the farmers far from markets.

Table 3. Estimates of the probit regression model on adoption of improved fallows in cotton producing areas of Zambia

Variable name	**Coefficient**	**Marginal effects (dy/dx)**
Household size	-0.191 (0.1311)	-0.071 (0.4902)
Labour in full time equivalents	0.087 (0.1340)	0.032 (0.0501)
Gender of the hh head	-0.013 (0.216)	-0.013 (0.08143)
Age of the hh head	0.012**(0.00512)	0.0044 (0.00191)
Education level of hh head	0.084***(0.0204)	0.032 (0.00761)
Marital status of the hh head (=1 if single, 0 otherwise)	-0.07 (0.071)	-0.025 (0.027)
Cultivated area for cotton	0.264***(0.092)	0.099 (0.0342)
Land holding size per capita	-0.731***(0.1389)	-0.273(0.05132)
Secure land tenure (=1 if yes, 0 otherwise)	-0.085 (0.18)	-0.032 (0.07)
Value of productive assets per capita	0.025**(0.0134)	0.01 (0.005)
Price infor access (=1 if yes, 0 otherwise)	0.22 (0.174)	0.082 (0.0654)
Cooperative group member (=1 if yes, 0 otherwise)	0.25 (0.1347)	0.093 (0.050)
Women's group member (=1 if yes, 0 otherwise)	0.126 (0.16)	0.05 (0.06)
Saving group member (=1 if yes, 0 otherwise)	-0.086 (0.2173)	-0.032 (0.0812)
Distance to the market (km)	0.010***(0.002)	0.004 (0.00075)
Seedlings from government (=1 if yes, 0 otherwise)	2.12***(0.49)	0.624 (0.053)
Advice on improved fallows (=1 if yes, 0 otherwise)	0.42***(0.14)	0.156 (0.049)
Belief in witchcraft for success(=1 if yes, 0 otherwise)	0.053 (0.04487)	0.02 (0.0167)
Belief in prayer than hard work for success (=1 if yes, 0 otherwise)	0.014 (0.0427)	0.005 (0.016)
Deastern	-0.468(0.284)	-0.181 (0.111)
Dmuchinga	0.964*(0.417)	0.3694 (0.1442)
Dsouthern	-0.27(0.329)	-0.097 (0.1104)
Constant	-1.39 (0.9004)	
Observations		1,203
Log likelihood		-276.5

Robust standard errors in parenthesis

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

Source: Author's own calculation-RALS 2015

As expected, receiving seedlings from government projects and improved fallow technique advice increases the probability of improved fallow adoption by 62.4% and 15.6%, respectively. It should be noted that there were some farmers who received seedlings and advice on improved fallows but did not adopt the technique. With the culture of input subsidies still rife among farmers, the free provision of inputs such as seedlings would definitely increase the adoptability potential of the improved fallows. Similar results were obtained by Nyoka *et al.,* (2011) and Kabwe (2010). The positive relationships between receiving improved fallow technique advice and adoption of the technique amplifies the importance of knowledge sharing on technologies taken to farmers. Several studies (Mwase *et al.*, 2015; Nyoka *et al.*, 2011; Solomon *et al*., 2011; Kwesiga *et al.*, 2003; Adesina *et al.*, 2000) have shown that there is a positive relationship between information on the technology and adoption of the technology. In terms of the farmer's location, the results showed that farmers in Muchinga Province were significantly more likely to adopt the improved tree fallows on cotton production compared to central Province which was used as a base region. Cotton farmers in Muchinga Province are 37% more likely to adopt the improved fallows.

An increase in land size per capita was found to significantly affect negatively the adoption of improved fallows among cotton farmers. An increase in landholding size per capita by one hectare reduces the probability of improved fallow adoption by 27.3%. The negative relationship between land holding size per capita and improved fallow adoption may possibly be because an increase in land owned by the farmers makes management to be difficult, hence they are less likely to venture into extra farm activities like planting of the improved fallows.

3.3 Cotton Yields and Sales Differences between Adopters and Non-adopters of Improved Fallows

The cotton yields and sales of the improved fallow adopters and non-adopters are shown in Table 4. Descriptive analysis shows significant differences in the cotton yields and value of cotton sales between adopters and non-adopters. Adopters of the improved fallows had significantly higher cotton yields and revenue from cotton sales. Without controlling for confounding factors, it is difficult to attribute these differences to improved fallow adoption.

Table 4. Average Differences in several outcome variables between adopters and non-adopters

	Adopters(n=208)	Non-adopters(=998)	Min difference	*t*-stat
Cotton yield(kg ha^{-1})	1290.459 (51.0)	1034.51 (20.93)	256 (55.08)	- 4.64
Cotton sales at actual price (ZMK)	2985.9 (151.0)	2400.9 (70.135)	585 (166.485)	-3.513

Equal variance not assumed, figures in parentheses are standard errors of the mean

Source: Author's own Analysis-RALS 2015

3.4 Impact of Improved Fallow Adoption after Controlling for Observable Factors

Out of the numerous existing methods of impact evaluation, this paper favors to use the PSM model for the reason that it is not dependent on the functional form and distributional assumptions. The method also helps in comparing the observed outcomes of technology adopters with the outcomes of counterfactual non-adopters (Heckman et al., 1998). The propensity scores in this study were estimated for improved tree fallow adopters and non-adopters by using the probit model. In this study, several models of Propensity Score Matching (PSM) models were tried out till the most comprehensive and robust specification that fulfilled the balancing tests and the establishment of the common support region was obtained. The PSM model results for improved fallow adoption are shown in Table 5. Variables that were significant for the estimation of the propensity score included: age of the household head, formal education level of the household head, area for cotton planting, distance to the market in kilometers, receiving improved fallow seedlings from government projects, receiving advice on improved tree fallows, having information on agroforestry trees, land size per capita and the farmers being located in Muchinga Province. All observations that did not meet the conditions of the common support region were dropped from analysis. This was done in order to improve on the quality of results obtained from both the PSM and ESR models. About 1203 observations fell within the common support region.

Table 5. Estimated propensity score model results for improved tree fallow adoption

Variables	Coefficient	Standard error	Z
Gender of the household head	-0.352	0.216	-0.16
Household size	-0.191	0.131	-1.46
Age of the household head	0.120*	0.005	2.34
Formal education level of the household head	0.0846***	0.02	4.14
Cultivated area for cotton	0.2636***	0.092	2.88
Land tenure	-0.09	0.177	-0.48
Cooperative member	0.25	0.1347	1.86
Price infor access	0.221	0.175	1.26
Women group member	0.126	0.158	0.8
Saving group member	-0.086	0.217	-0.4
Distance to the market(km)	0.104***	0.002	5.2
Seedlings from government	2.12***	0.485	4.36
Advice on improved fallows	0.42***	0.135	3.11
Labour in fulltime equivalents	0.087	0.134	0.65
Value of productive assets per capita	0.0254	0.0133	1.91
Land size per capita	-0.7312***	0.139	-5.26
Belief in witchcraft for success	0.053	0.045	1.18
Belief in prayer than hard work for success	0.0138	0.0427	0.32
Dsouthern	-0.273	0.329	-0.83
Deastern	-0.4688	0.285	-1.65
Dmuchinga	0.964*	0.42	2.31
Constant	-1.3954	0.9004	-1.55
Observations	1, 203		
LR Chi2(22)	179.33		
Prob> chi2	0.000		
Pseudo R2	0.2499		

*, **, *** significant difference between adopters and non-adopters mean at 90, 95 99% significance level

Source: Author’s own calculation-RALS 2015

The propensity scores were used to estimate the ATTs emanating from adoption of improved fallows in the cotton producing areas of Zambia. Results from the two matching algorithms, the nearest neighbour and the kernel matching approaches are shown in Table 6. In both cases, there is evidence that controlling for observable covariates, the technique does increase cotton yields and income from cotton sales. The adoption of improved fallows in cotton production increased cotton yields by about 279 kg ha^{-1} and 302 kg ha^{-1} when estimated using the nearest neighbour and kernel matching algorithms, respectively. The technique also increased cotton income by about ZMW 822 ha^{-1} and ZMW 793 ha^{-1} when estimations were done by the nearest neighbour and kernel matching respectively.

Table 6. ATT estimation of various outcome variables using nearest neighbour matching

	ATT	**Bootstrapped standard error**	**t-stat**
Nearest Neighbour			
Yield of cotton (kg ha^{-1})	279.2	88.2	3.17
Value of cotton sales at actual price (ZMW ha^{-1})	822.06	245.97	3.34
Kernel Matching			
Cotton yield per hectare (kg ha^{-1})	302.2	60.14	5.00
Value of cotton sales at actual price(ZMW ha^{-1})	792.7	167.92	4.72

Number of treated units=188 and number of control units=345 for both algorithms

Source: Author’s own calculation-RALS 2015

3.5 Impact of Improved Fallow Adoption after Controlling for Unobservable Factors

In the Tables, 7 and 8, the full information maximum likelihood estimates of the endogenous switching regression model are shown. The first and second columns in both tables show the welfare functions (cotton yield and value of cotton sales) for households that did and did not adopt the improved fallow technique while the column at the end represent the instrument variable used in the selection equation on adoption of improved fallows. Receiving tree seedlings from the government was highly correlated with adoption of improved fallows while it was uncorrelated with either cotton yields or income from cotton sales. This variable therefore was a suitable instrument in both models. The correlation coefficient between the adopter's regime and the selection equation in the cotton yields model was negative and significantly different from zero. This means that farmers who adopted improved fallows got higher cotton yields than a randomly selected farmer from the sample would have achieved. There exist both observed and unobserved factors influencing the decision to adopt improved fallows and this welfare outcome given the adoption decision.

Table 7. Full information maximum likelihood estimates of the switching regression model on cotton yield

Variables	**Yieldctn0**	**Yieldctn1**	**Selection**
Gender of the hh head	258.4**(109.9)	266 (176.1)	
Household size	-139.7**(67.56)	142.5 (112.5)	
Age of the hh head	-2.675 (2.702)	0.0326 (4.413)	
Education level of hh head	6.595 (10.56)	7.431 (16.34)	
Marital status of the hh head	102.1***(37.73)	62.2 (56.44)	
Cultivated area for cotton(ha)	-222.1***(47.68)	-181.7***(68.73)	
Cooperative member	-45.93 (71.88)	-152.3 (110.9)	
Price infor access	57.9 (95.43)	109.5 (143.5)	
Women's group member	-115.6 (77.23)	219.9* (129.8)	
Savings group member	-176.4 (115.3)	358.1**(180.2)	
Distance to the market (Km)	0.74 (1.446)	0.116 (1.136)	
Advice on Improved fallows	173.9**(67.97)	81.96 (113.9)	
Labour in full time equivalents	156.6**(69.34)	-164.3 (114.2)	
Value of productive assets per capita	5.006 (5.354)	6.289 (12.69)	
Landholding size per capita	-5.37 (49.04)	-135.2(125.2)	
People in this area use witchcraft to become successful.	18.71 (23.67)	-12.4 (36.74)	
Prayer is more important than hard work for success.	-49.56**(21.59)	9.207 (36.1)	
Dsouthern	52.16 (198.4)	-114.5 (271.3)	
Deastern	117.2 (170.8)	218.9 (245.6)	
Dmuchinga	610.4**(307.4)	371 (292.7)	
Seedlings from government or projects,1=yes			2.095***(0.484)
Constant	1,119***(424.4)	127.8 (702.1)	-0.376***(0.0557)
rho 0	0.0956	0.2521	
rho 1	-0.2852	0.224	

Dependent variable: Cotton yield per hectare (kg ha^{-1})

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

source: Author's own Calculation-RALS 2015

Table 8. Full information maximum likelihood estimates of the switching regression model on value of cotton sales

Variables	**value of cotton sales 0**	**value of cotton sales 1**	**Selection**
Gender of the hh head	449.4*(231.9)	777.4*(418.5)	
Household size	-301.1**(142.7)	302.5 (267.5)	
Age of the household head	-4.278 (5.695)	-10.82 (10.490	
Education level of household head	12.89 (22.26)	29.49 (38.81)	
Marital status of the household head	201.9**(79.55)	3.951 (134.2)	
Cultivated area for cotton (ha)	1,239***(100.7)	1,469***(163.8)	
Cooperative member	-264.8*(151.8)	-427.1 (264.1)	
Price infor access	-63.32 (201.2)	43.30 (340.6)	
Women group member	7.899 (162.8)	402.3 (307.6)	
Saving group member	-553.7**(243.0)	605.3 (428.9)	
Distance to the market(Km)	0.143 (3.048)	0.533 (2.695)	
Advice on Improved fallow	247.5*(143.5)	108.5 (270.3)	
Labour in full time equivalents	367.5**(146.6)	-283.2 (271.5)	
Value of productive assets per capita	19.87*(11.29)	50.17*(30.18)	
Landholding size per capita	18.17 (103.4)	582.0*(297.5)	
Belief in witchcraft to become successful.	-5.119 (49.89)	-107.5 (87.34)	
To be successful, prayer is more important than hard work.	-75.15*(45.54)	-24.53 (85.78)	
Dsouthern	-839.8**(420.1)	-140.0 (644.4)	
Deastern	-490.3 (360.1)	1,198**(581.9)	
Dmuchinga	61.99 (648.0)	1,613**(694.1)	
Seedlings from government or projects,1=yes			2.067***(0.472)
Constant	1,913**(973.4)	-875.1 (1,663)	-0.38***(0.056)
rho 0	0.01052	0.5768	
rho 1	-0.31657	0.2114	

Dependent variable: Value of cotton sales at actual price(ZMW)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's own calculation-RALS 2015

The switching regression model's results on the expected welfare outcomes of yield and income under actual and counterfactual conditions are shown in Table 9. The results show that adopters who decided to adopt the technology had significant higher yields than in their counter factual state i.e. had they not adopted. This result suggests that improved fallows have a positive effect on cotton yields. Those who adopted the technique increased cotton yields by 188.5kg solely as a result of using improved fallows. Earlier studies by other authors such as (Obuoyo and Ochola ,2015; Place *et al.*, 2005; Kuntashula & Mungatana, 2014) obtained similar results on crop yield increases other than cotton. Similarly estimates on the value of cotton sales show that adopters significantly gain as a result of using improved fallows. The causal effect of the technique per hectare was estimated at around ZMW 500. For the non-adopters, the predicted estimates show that they could have obtained lower cotton yields had they adopted the technique. However, the yield difference between non-adopters and had they adopted was statistically insignificant. The difference in the value of cotton sales/ha between non-adopters and their counterfactual state was equally statistically insignificant. Given their unobservable characteristics, perhaps this could be one reason why the non-adopters did not adopt in the first place.

Table 9. Endogenous switching regression model results

	Decision Stage		Treatment effect
	Adopted	Not to adopt	Difference(TT or TU)
Cotton yield per hectare(Kg ha^{-1})			
Adopters	1479.1	1290.6	188.5***
Non-adopters	988.2	1018.5	-30.3
Heterogeneity effects	$BH_{1=}$ 490.9	BH_2 = 272.1	TH=218.7
Value of cotton sales at actual price(ZK)			
Adopters	3486.7	2985.9	500.7***
Non-adopters	2246.3	2193.2	53.1
Heterogeneity effects	BH_1=1240.3	BH_2=792.7	TH=447.6

Source: Author’s own calculation-RALS 2015

Note: TT treatment effect on the treated (adopting–had not adopted), TU treatment effect on the untreated (had they adopted–not adopted), BH Base heterogeneity (adopted–had they adopted), TH Transitory heterogeneity (TT–TU).

4. Conclusion and Policy Implications

Evaluation of sustainable land management practices such as the improved fallows in sub Saharan Africa has mostly been conducted on the staple maize crop. We assessed the factors affecting adoption and estimated the causal effect of improved fallows on a cash crop, cotton among the cotton producing farmers in Zambia. We used probit regression and propensity score matching techniques complemented with endogenous switching regression models in our estimation. Factors which were identified to positively affect the adoption of improved fallows include membership to a cooperative, receiving improved fallow seedlings from the government projects and having information on agroforestry trees, an increase in age of the household head, education level of the household head, productive assets per capita, cultivated area for cotton and distance to the market. On the other hand, an increase in land size per capita was found to negatively affect the adoption of improved fallows among cotton farmers.

Both the propensity score matching and endogenous switching regression suggest that the improved fallow adoption significantly increased the farmer’s cotton yields and value of cotton sold at actual prices and eventually increased the farmer’s cotton income. This was particularly true for the adopters of the technique. For the non-adopters, predicted results showed that controlling for unobservables, the technique had no significant influence on these outcome variables. In this case, the finding seems to suggest the importance of discovering the hidden role of unobservable characteristics in influencing adoption and impact of technologies. In addition to what is observed or measured, more differences are likely to exist between the adopters and the non-adopters of improved fallows in the cotton producing areas of Zambia. Thus, more detailed anthropological studies might help in untangling the equally underlying factors that influences the impact of the improved fallows in cotton production.

Given the positive impacts of improved fallows on cotton production among the adopters, the study recommends that the government should explicitly promote the techniques to be used in cotton production in addition to the common practice of promoting it on maize. This could be done through improving extension services and messages, and continuous training farmers on the use of innovative techniques such as improved fallows. Providing the farmers with improved fallow seedlings alongside an increase in productive assets enhance the probability of adoption thus just like is the case with the fertiliser subsidies, the government should consider expanding the subsidies on improved fallow seedlings. The farmers’ formal education levels should be improved as it was found in this study that an improvement in the farmers ’s formal education level increased their adoption of improved fallows.

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