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Estimating the causal effect of sustainable agriculture intensification adoption on agricultural land expansion in Katete district of Zambia: An endogenous switching regression analysis

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ABSTRACT

Forest land cover is declining at an alarming rate in Zambia and this poses a threat to the elimination of major ecosystem services. Identification of sustainable agricultural intensification (SAI) practices presents an opportunity to reduce pressure on forest land resources. The objective of this study was to estimate the causal effect relationship between SAI practices adoption and farmland expansion using the Endogenous Switching Regression model. A cross-sectional survey conducted in 2020/21 season using a random sample of 300 farm households was used to assess the effect of SAI practices adoption on farmland expansion. The causal impact estimation revealed that the adoption of SAI practices reduced expected land expansion on one hand, while the opposite was true for the non-adoption of SAI practices. The findings also indicate that increasing the area under cropping, farmer affiliation to farmer associations, and participation in agricultural extension training are positive precursors to increasing the probability of adopting SAI practices at the farm level. Additionally, the more educated a farmer is, coupled with older age reduces the probability of engaging in farmland expansion. These two variables point to the role and importance of increased farming experience and knowledge in mitigating agricultural farmland expansion. This finding suggests that the mitigation of agricultural productivity challenges through technology dissemination should be coupled with farmer education. The results from this study, therefore, generally confirm the potential positive impact of SAI technology adoption on reducing agricultural farmland expansion among smallholder farmers which translates into increased conservation of natural resources, especially forests.

Keywords: Adoption, agricultural land expansion, binary variable, endogeneity, endogenous switching, forestry, Katete, Sustainable Agriculture Intensification

RÉSUMÉ

La couverture forestière diminue à un rythme alarmant en Zambie, ce qui représente une menace pour l'élimination des principaux services écosystémiques. L'identification des pratiques d'intensification agricole durable (IAD) présente une opportunité de réduire la pression sur les ressources forestières. L'objectif de cette étude était d'estimer la relation d'effet causal entre l'adoption des pratiques d'IAD et l'expansion des terres agricoles en

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utilisant le modèle de régression endogène par commutation. Une enquête transversale menée en 2020/21 auprès d'un échantillon aléatoire de 300 ménages agricoles a été utilisée pour évaluer l'effet de l'adoption des pratiques d'IAD sur l'expansion des terres agricoles. L'estimation de l'impact causal a révélé que l'adoption des pratiques d'IAD réduisait l'expansion attendue des terres d'une part, tandis que le contraire était vrai pour la non-adoption des pratiques d'IAD. Les résultats indiquent également que l'augmentation de la superficie cultivée, l'affiliation des agriculteurs à des associations d'agriculteurs et la participation à des formations en extension agricole sont des précurseurs positifs pour augmenter la probabilité d'adoption des pratiques d'IAD au niveau de l'exploitation agricole. De plus, plus un agriculteur est éduqué, associé à un âge plus avancé, moins il est probable qu'il s'engage dans l'expansion des terres agricoles. Ces deux variables soulignent le rôle et l'importance de l'expérience et des connaissances agricoles accrues dans l'atténuation de l'expansion des terres agricoles. Cette constatation suggère que l'atténuation des défis de productivité agricole par la diffusion de la technologie devrait être couplée à l'éducation des agriculteurs. Les résultats de cette étude confirment donc généralement l'impact positif potentiel de l'adoption de la technologie d'IAD sur la réduction de l'expansion des terres agricoles chez les petits agriculteurs, ce qui se traduit par une conservation accrue des ressources naturelles, en particulier des forêts.

Mots-clés: Adoption, expansion des terres agricoles, variable binaire, endogénéité, commutation endogène, foresterie, Katete, Intensification de l'Agriculture Durable

INTRODUCTION

The quest of meeting food needs especially for maize amidst the challenges of a growing population coupled with declining soil fertility mainly due to poor agronomic practices is putting a lot of pressure on the natural resources in Sub-Saharan Africa (SSA) (Epule, 2022). Deteriorating soil health poses a global challenge in the context of food insecurity, climate change and environmental degradation (McBratney *et al.,* 2014). In SSA, maize is the second most cultivated crop among smallholder farmers who do not have adequate access to capital to invest in modern yield improvement methods. As a result, agriculture is marked by low productivity with little application of science and technology and farmers often resort to increasing the area under production by opening up of relatively fertile new forest fields in a bid to increase production (Chauvin, 2012; Shukla, 2019; Flammini, 2022). Therefore, in order to compensate for low productivity and production in the region, the doubling of agricultural food production during the past decades was associated with an increase in land area under cultivation through the practice of opening up new virgin land in form of agricultural expansion, a situation that has been threatening the eco-system services, biodiversity, resilience to climate change, and forest resources (Tilman, 1999). Expanding agriculture area into forests accounts for about 80% of the deforestation globally and it is the main cause of tropical deforestation (Kaimowitz and Angelsen, 1998). Pressure to open up new land for agricultural purposes is still increasing as a result of soil degradation, socio-economic strains such as poverty, increased population as a result of internal and regional migration, smaller farm sizes and the increase in commodity prices (Angelsen, 1999; Wynants, 2019). The opening up of new land through shifting cultivation at the expense of the forest is unsustainable, and only satisfactory in regions where the population is sparse and there is plenty of land, which can be fallowed for many years (Fleeskens, 2010; Ngoma *et al*., 2019). Poor access to agricultural extension and advisory services is among the factors that are reducing productivity and yields for the major crops such as maize (*Zea mays* L.) in Sub-Saharan Africa (Di Falco, 2014). Good agricultural practices can improve the sustainability of agriculture on a number of fronts, including protecting environmental and natural resources (Hobbs, 2003).

In the Zambian context, forest land cover is declining at an alarming rate and is threatening the elimination of major ecosystem services (Matakala *et al.,* 2015). While increasing production is necessary to feed a growing population and meet changing dietary preferences, basing this on expanding area at the expense of the forest is unsustainable, given the increasing land scarcity and population growth (Ngoma, 2019). The annual deforestation rate in Zambia is 276,021 ha per annum or 6% of the total forest cover (GRZ *et al.,* 2017). Between 2000 and 2014, crop production related agricultural expansion in Zambia was one of the key contributing factors to the total forest loss that ranged between 250,000 and 300,000 hectares per year during the period, representing an average annual loss rate of 0.7 percent of the forestry reserves (Matakala *et al.,* 2015). This percentage is significantly higher than the global rate of deforestation and forest loss, which was estimated to be 0.25 percent in 2015. Results of deforestation analysis indicate that 102,087 ha of forests were lost in the Eastern Province of Zambia between 2010 and 2014 which is equivalent to an average annual deforestation rate of 0.9% in 2010-2014 (Wathum *et al.,* 2016). Furthermore, the same study indicated that the Eastern Province of Zambia has been contributing significantly to this forest loss and roughly 156,000 ha of forest were estimated to have been lost in the province during the period 2000 - 2015, with agricultural expansion accounting for about 10,036 ha (6.4%) of forest loss annually through the practice of shifting cultivation.

The agricultural sector has for years been battling with finding solutions to mitigate agricultural expansion in an effort to conserve the forest resources. Among the potential best bet options for mitigating agricultural expansion and raising crop productivity while conserving forest resources is the concept of Sustainable Agriculture Intensification (SAI) (Ngoma, 2019). In this context SAI is defined as a process or system where agricultural yields are increased without adverse environmental impact and without the conversion of additional non-agricultural land (Pretty, 2014). The commonly used SAI practices in Sub-Saharan Africa and Zambia in particular, include capitalization of soil fertility, use of new pesticides, agricultural extension training, use of indigenous and context-specific knowledge in local farming practices, growing crops and varieties that are tolerant to biotic and abiotic stresses, minimum tillage, use of cover crops, crop-livestock integration production practices, use of inorganic fertilizers, integrated pest and disease management and integrated weed management (Sanginga and Woomer, 2009).

In the context of econometric analysis, the welfare implications of agricultural technology pose at least two challenges: unobserved heterogeneity and possible endogeneity. There seems to be a two-way link between technology adoption and household well-being. Technology adoption may result in productivity enhancement for small producers and greater income, but it may also be that greater income leads to more technology adoption. In this paper, we take into account that the differences in cropland expansion variables between those farm households that did and those that did not adopt SAI practices could be due to unobserved heterogeneity. Not distinguishing between the casual-effect of technology adoption and the effect of unobserved heterogeneity could, indeed, lead to misleading policy implications. We account for the endogeneity of the adoption decision (that is, for the heterogeneity in the decision to adopt or not to adopt new technology and for unobservable characteristics of farmers and their farm) by estimating a simultaneous equation model with endogenous switching by full information maximum likelihood estimation.

The majority of research on SAI and agricultural land expansion has a global or national focus (Reardon *et al.,* 1999; Maertens, 2006; Jayne *et al.,* 2019). Others have less emphasis on specific theoretical frameworks to inform empirical study (Pretty, 1997; Rudel, 2020; Haggar *et al.,* 2021). The empirical evidence on the relationship between Sustainable agricultural intensification and agricultural expansion in Zambia is still scant, though similar studies have been done in other regions (Ceddia, 2013; Andersson Djurfeldt, 2020; Kansiime, 2022).

The objective of this study was to to estimate the causal effect relationship between SAI practices adoption and farmland expansion using the Endogenous Switching Regression model. Literature indicates that SAI has great potential to mitigate agricultural farmland expansion through the application of practices that yield economic crop productivity levels within existing fields without farmers resorting to opening up new fields in virgin land in search of relatively fertile land.

This study therefore aims to contribute to the literature on the causal-effect relationship between SAI practice adoption and farmland expansion among smallholder farmers based on the empirical analytical framework for Endogenous Switching Regression analysis. Assessing the impact of farm technology adoption can assist with setting priorities, providing feedback to the research programs, guide policy makers and those involved in technology transfer to have a better understanding of the way new technologies are assimilated and diffused into farming communities, and show evidence that clients benefit from the research products (Manyong *et al*., 2001).

RESEARCH APROACH

Study area. The study was conducted in two sites, namely Vulamukoko and Lukweta, that are located in Katete district of Eastern Province in Zambia. The district is located 32.0440^{o}E, 14.0584oS and stands at 1,060 m.a.s.l and is inhabited by a population of over 1.7 million people, with over 80% evident in rural areas (Zamstat, 2018). It has a geographical area coverage of 3,987 km^2. The two study sites were purposively selected to represent one near a protected area (Lukweta) and one far from a protected area (Vulamukoko). Lukweta area borders Chindindendi and Mulodzela protected forest areas where farmers have been encroaching on with farming activities (Figure 1). The initial forest reserve area for Chindindendi forest reserve was about 14,234,896 sq.m while that of Mulodzela was about 8,408,113 sq.m.

These forest reserves are among the 491 gazetted forest reserves in Zambia. Lukweta community has about 147 villages with a farm household population of over 6,500 farm families. Vulamukoko area is about 30 km from the nearest forest protected area. The area has 58 villages with a total of 3007 farm families.

Sample size and sampling procedure. A multi-stage random and non-random sampling procedure was used to select study households. The first stage involved purposive selection of communities based on the Sentinel project sites and close proximity to Chindindendi and Mulodzela protected forest areas and those which were further away. The second stage involved a probability sampling of study villages from the selected communities. A sample of 150 households from each of the two selected communities was selected giving a total sample size of 300 households for the study.

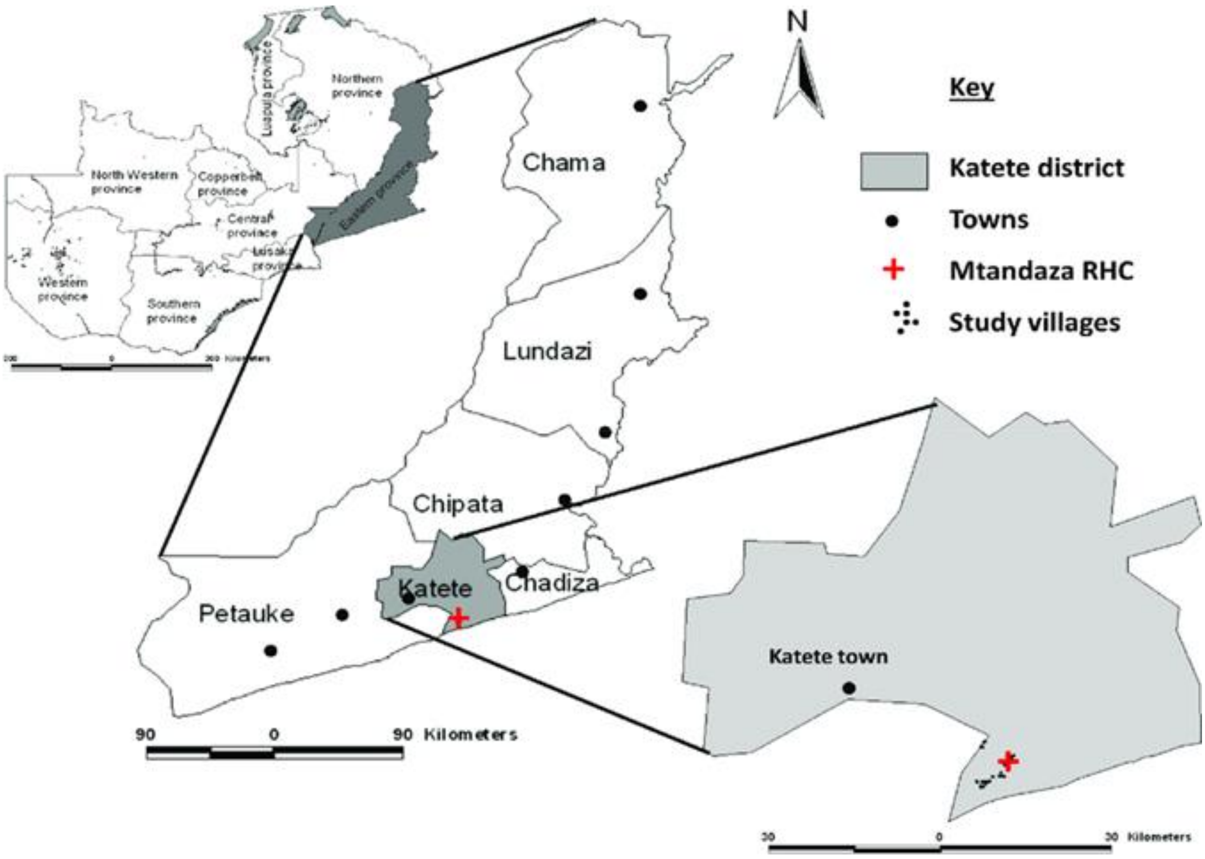

Figure 1. Location of Katete district in Zambia and research study sites

The sample size was determined using the Taro Yamane sampling technique which is mathematically presented as: n = N/1+N(e)2. Where, n is the desired study sample size, N is the whole population under study, and e is the precision or sampling error which is usually 0.10, 0.05 or 0.01 (Margin of error).

Research design, data collection and analysis. A cross-sectional study was conducted during the period of January – April 2021. The study used a mixed research method approach that involved the collection of both quantitative and qualitative data using a semi-structured questionnaire.

Qualitative methods involved focus group discussions with community leaders, key informant interviews with agricultural staff, as well as institutional heads for institutions that have a presence in the community. The study's focus was on the analysis of the potential of sustainable agricultural intensification practices in mitigating agricultural expansion among smallholder farmers. Particularly, identifying SAI practices that have a significant influence on agricultural expansion.

A structured questionnaire, literature review and a semi-structured checklist questionnaire where used in data collection. The thrust of the structured questionnaire was focused on household demographic characteristics, agricultural asset ownership, land characteristics and distribution, factors that lead to agricultural expansion, organizational affiliations, and training as well as data on sustainable agriculture intensification practices. A qualitative checklist was used to validate the information from the household interviews.

This study sought to assess the causal effect of SAI adoption on farmers' decisions to expand farmland. According to Hausman (1978) technology adoption in this case SAI practices adoption is either voluntary (endogenous) or some technologies are intended for a certain group of farmers hence the question of endogeneity of technology adoption arises. In this study, for instance, it is conceivable that productive farmers are much more willing to use SAI technologies. The source of endogeneity in this situation is self-selection for technology intervention, and if this is not taken into account, the genuine influence of the technology would be overstated. It is also likely that internal motivation may systematically differ between SAI adopters and non-adopters further leading to self-selection bias. Since the decision to adopt SAI is endogenously determined, the endogenous switching treatment effects regression (ESTER) approach was adopted to create a counterfactual framework under which the causal effect of SAI adoption on agricultural land expansion could be estimated. Under the ESTER framework, the adoption of SAI technologies was the switching parameter. The ESTER approach has been used in recent studies to determine the treatment effects when the treatment variable is endogenous (Asfew and Bekele, 2010; Kuntashula and Mungatana, 2013; Abdulai, 2014; Akpalu and Normanyo, 2014).

We followed Lokshin and Sajaja (2004) approach to specify the ESTER model. The ESTER is a two-step estimation framework where the first step involved estimating a selection equation (SAI adoption) that describes the technology adoption behaviors of maize farmers as they make the decision to adopt SAI practices or not. The selection equation was defined as in equation 1.

$$G_i^* = \alpha Z_i + \mu_i \ \ with\ G_i = \begin{cases} 1\ if\ G_i^* > 0 \\ 0\ otherwise \end{cases} \qquad (1)$$

where G_i^* the unobserved SAI technology adoption and G_i is the observed technology adoption which is the dependent variable (SAI adoption) which equals one if the farmer has adopted and zero otherwise. α is a vector of parameters to be estimated, Z_i is a set of observed farm and non-farm characteristics determining adoption and μ_i captures the random disturbances associated with SAI adoption. The first step facilitates the estimation of the inverse Mills ratio (Akpalu, 2014) which is used as a selection bias control variable in the second step of the ESTER analysis framework.

The second part of the ESTER analysis framework is to estimate two expansion into forest land outcome continuous regression equations where farmers face the regimes of adopting or not adopting SAI practices (Equations 2 and 3) from which the drivers of agricultural land expansion were also determined.

Regime 1 (Adopters):

$$y_{1i} = \beta X_{1i} + \varepsilon_{1i} \quad if\ G_i = 1 \qquad (2)$$

Regime 0 (Non-adopters):

$$y_{2i} = \beta X_{2i} + \varepsilon_{2i} \quad if\ G_i = 0 \qquad (3)$$

where y_i is agriculture agricultural land expansion in regimes 1 (adopt) and 2 (not adopt). X_i are vectors of exogenous variables (control variables) expected to influence agricultural land expansion, β is a set of parameters to be estimated, and ε_i is the random disturbance under respective regimes.

In this study, the main outcome, y, agricultural land expansion is continuous. The switching/ selection variable, which is to adopt SAI practices or not adopt is a binary variable. There may be non-zero covariances between the error terms of the adoption decision equation and the outcome equation as a result of self-selection into adopters or non-adopter category. This suggests that sample selection bias would affect the βn and βo ordinary least squares (OLS) estimates since the error terms in Equation (2) have non-zero expected values when conditional on the sample selection criterion (Lee 1978; Maddala, 1983). Lee (1978) views sample selection as a problem with a missing variable. The trivariate normal distribution with zero mean and non-singular covariance matrix stated in equation 4 is assumed to apply to the error terms ε_c, ε_n, and ε_0.

$$cov(\varepsilon_n, \varepsilon_0, \varepsilon_c = \begin{pmatrix} \sigma_n^2 & \sigma_{no} & \sigma_{nc} \\ \sigma_{no} & \sigma_o^2 & \sigma_{oc} \\ \sigma_{nc} & \sigma_{oc} & \sigma_c^2 \end{pmatrix} \quad (4)$$

where σ_c^2 is the variance of the error term ε_c in the criterion equation (i.e., technology adoption); σ_n^2 is the variance of ε_n; σ_n^2 is the variance of ε_0; σ_no is the covariance of ε_n and ε_0; σnc is the covariance of εn and ε_c; and σ_{oc} is the covariance of ε_0 and ε_c. It can be assumed that $\sigma^2 = 1$, since α is estimable only up to a scalar factor. In this analytical framework, the study similar methods that were applied in other studies (Johnson and Kotz, 1970; Abdulai, 2014). Given these assumptions, according to these past studies, the expected values of the truncated error terms (ε_n $|G_i = 1$) and (ε_o $|G_i = 0$) are then given as in equations 5 and 6:

$$E(\varepsilon_n\,|G_i = 1) = E(\varepsilon_n|\varepsilon > -\beta'\alpha = \sigma_{nc}\frac{\emptyset(\beta'\alpha/\sigma)}{\Phi(\beta'\alpha/\sigma)} \equiv \sigma_{nc}\lambda_n, \quad (5)$$

$$E(\varepsilon_n\,|G_i = 0) = E(\varepsilon_n|\varepsilon \le -\beta'\alpha = \sigma_{oc}\frac{\emptyset(\beta'\alpha/\sigma)}{1-\Phi(\beta'\alpha/\sigma)} \equiv \sigma_{oc}\lambda_o, \quad (6)$$

where Ø and ϕ are the probability density and cumulative distribution functions of the standard normal distribution, respectively. The ratio of Ø and ϕ evaluated at β'α is the inverse Mills ratio [λ_n and λ_o in Equations (4) and (5)]. The terms λ_n and λ_o can be treated as missing variables in Equation (2) to account for selection bias.

The estimation of the model proceeds in two stages. The first stage involves a probit regression to determine the probability of adoption and thus estimation of the parameter β given in equation [1]. These estimates are then used to calculate the selectivity terms (λ_n, λ_o) according to equations [4] and [5]. The drawback of this two-step approach is that it generates residuals that are heteroskedastic and as a result cannot be used to obtain consistent standard errors without cumbersome adjustments (Lokshin and Sajaia, 2004). The full information maximum likelihood method suggested by Lokshin and Sajaia (2004) overcomes the problem through a simultaneous estimation of the two equations, that is, the adoption and outcome equations. Of particular interest are the signs and significance levels of the correlation coefficients (ρ) from the estimates. As indicated previously, these are the correlations of the error terms of the outcome and choice equations (*corr(ε,u) = ρ*). Specifically, there is endogenous switching, if either ρ_A ($\sigma_{A\varepsilon}/\sigma_A\ \sigma_\varepsilon$) or ρ_N ($\sigma_N/\sigma_A\ \sigma_\varepsilon$) is significantly different from zero, which would result in selection bias. If ρ>0, this would imply negative selection bias, indicating that farmers with below average yields and net returns are more likely to adopt the technology. On the other hand, ρ<0 implies positive selection bias, suggesting that farmers with above average yields and net returns are more likely to adopt the technology.

In the second stage of the ESTER analysis framework, these predicted variables are added to the appropriate equation in (2) to yield equation 7.

$$y_{1i} = \beta X_{1i} + \sigma_{nc}\lambda_n + \varepsilon_{1i} \quad if\ G_i = 1 \quad \text{and}$$

$$y_{2i} = \beta X_{2i} + \sigma_{oc}\lambda_o + \varepsilon_{2i} \quad if\ G_i = 0 \quad (7)$$

where _1i and _2i have zero conditional means. These residuals are, however, heteroscedastic (Maddala, 1983). The coefficients of the variables λ_n and λ_o provide estimates of the covariance terms σ_{nc} and σoc, respectively. Since the variables λ_n and λ_o have been estimated, however, the residuals ε_{1i} and ε_{2i} cannot be used to calculate the standard errors of the two-stage estimates. Studies applying endogenous switching have followed Maddala (1983) procedure for estimating the correct variance–covariance matrix. However, this procedure requires potentially cumbersome adjustments to derive consistent standard errors, because the correct variance–covariance matrix of the estimates is very complicated (Lee, 1978). Freeman *et al*. (1998) used weighted least squares to account for heteroscedastic errors; however, the use of weighted least squares is limited only to situations where the exact form of heteroscedasticity is known, which is rarely the case. A more efficient version of the endogenous switching model is estimated by full information maximum likelihood (FIML) method (Greene 2000; Lokshin and Sajaia 2004). The FIML method simultaneously estimates the probit criterion or selection equation and the regression equations to yield consistent standard errors. Given the assumption of trivariate normal distribution for the error terms, the logarithmic likelihood function for the system of Equations (1) and (2) can be given as (Lokshin and Sajaia, 2004).

$$lnL = \sum_{i=1}^{N}\{ G_i w_i [lnF\left(\frac{(\beta_i'\alpha + \rho_{nc}(Y_{ni} - X_{ni}'\beta)/\sigma_{n})}{\sqrt{1-\rho_{nc}^2}}\right) +$$

$$\ln(f((Y_{ni} - X_{ni}'\beta)/\sigma_n)/\sigma_n)] +$$

$$(1 - G_i)w_i[\ln(1 - \mathrm{F}\left(\frac{(\beta_i'\alpha + \rho_{oc}(Y_{oi} - X_{oi}'\beta)/\sigma_{o})}{\sqrt{1-\rho_{0c}^2}}\right) +$$

$$\ln(f(Y_{oi} - X_{0i}'\beta)/\sigma_{o})/\sigma_o)]\}$$

where f and F are the probability density and cumulative distribution functions of the standard normal distribution, respectively; w_i is an optional weight for observation i (i = 1,2,...,N) and $\rho_{nc} = \sigma_{nc}/\sigma_n \sigma_c$ is the coefficient of correlation between ε_n and ε_c and $\rho_{oc} = \sigma_{oc}/\sigma_o \sigma_c$ is the coefficient of correlation between ε_o and ε_c. To make sure the estimated ρ_{nc} and ρ_{oc} are bounded between 1 and 1 and the estimated σ_n and σ_c are always positive, the maximum likelihood directly estimates ln σ_n, ln σ_c, and a tanh ρ_{jc} where a tanh $\rho_{jc} = ½ \ln [(1 + \rho_{jc})/(1 - \rho_{jc})]$.

The signs of the correlation coefficients ρ_{nc} and ρ_{oc} have economic interpretations (Fuglie and Bosch, 1995). If ρ_{nc} and ρ_{oc} have alternate signs, then individuals adopt new technology on the basis of their comparative advantage: those who adopt have above-average returns from adoption and those who choose not to adopt have above-average returns from non-adoption. The opposite is true if the coefficients have the same sign, which denotes hierarchical sorting: adopters benefit from adopting since their returns are above average whether they do so or not, and non-adopters benefit from not adopting because their returns are below average in both cases. The selection equation was used to fit the model since the outcome variable was dichotomous in nature.

RESULTS

Socio-economic characteristics of the study population by SAI adoption. Study findings show that there was a significant statistical difference (at 95% confidence level) between households in terms of adoption of SAI practices and involvement in farmland expansion. Results reveal that 29 percent of the sampled farm households were involved in farmland expansion and were also adopters of SAI practices. On the contrary, 57 percent were non-adopters of SAI practices but had expanded their farmland in the study period 2015-2020.

Access to physical assets reveals a higher level of cattle ownership among SAI practices adopters (77 percent) compared to 61 percent ownership for the non-adopters of SAI. Similarly, results reveal statistically significant differences in terms of agricultural land ownership with SAI adopters owning more land (5.44ha) compared to non-adopters who own an average of 4.97ha.

Results show that 69 percent of the non-SAI adopting households were expanding their farmlands due to limited cash to purchase inorganic fertilizers compared to 56 percent for the SAI adopters. This finding collaborates with those of Lee (2005) who reported that smallholder farmers are likely to adopt natural resource management interventions such as SAI practices only when the additional benefits from such investments outweigh the added costs. Climate change is another variable that was reported to be contributing to farmland expansion. Results showed statistically significant differences with 10 percent of the non-adopters of SAI practices reporting engagement in farmland expansion due to climate change as opposed to 7 percent of the adopters. Interestingly, a higher percentage (86 percent) of the farm households that received agricultural extension training were involved in farmland expansion compared to 50 percent for the non-adopters of SAI practices.

Table 1. Definitions and summary statistics of the variables used in the analysis, by household SAI adoption

Definition	SAI Adopters (n= 139)		SAI non-adopters (n= 109)		P-value (α = 0.05)
	Mean	Std. Dev.	Mean	Std. Dev.	
Dependent variables					
Adoption of SAI Practices					
Field area associated with expansion of farmland between 2015 – 2020 in Ha	1.31	2.546	2.07	2.3029	0.016**
Independent variables					
Household size	6.54	2.141	6.54	2.810	0.996
Number of household members between 16-59 years old	2.89	1.413	3.07	1.631	0.350
Age of household head in years	43.83	11.196	44.07	13.102	0.874
Years of farming	20.64	11.307	20.55	12.144	0.952
Household head ability to read and write (yes=1, 0=no)	0.80	0.403	0.70	0.462	0.066
Household ownership of cattle (=1 if household owns cattle, =0 if does not own cattle)	0.77	0.422	0.61	0.489	0.008**
Total farmland size own (ha)	5.44	5.711	4.97	2.871	0.009**
Total cropped field size in the study year 2019/20 season (ha)	3.89	2.727	3.169	2.136	0.025**
Expanded farmland due to declining soil fertility (1=yes, 0 otherwise)	0.76	0.435	0.82	0.385	0.417
Expanded farmland due to some crops that require relatively new fields to perform well (1=yes, 0 otherwise)	0.44	0.502	0.61	0.491	0.084

Expanded farmland due to high requirement for higher fertilizer dosage in old fields (1=yes, 0 otherwise)	0.54	0.505	0.71	0.458	0.074
Expanded farmland due to lack of adoption of other sources of fertility improvement methods (1=yes, 0 otherwise)	0.32	0.471	0.65	0.482	0.001**
Expanded farmland due to limited cash to purchase fertilisers (1=yes, 0 otherwise)	0.56	0.502	0.69	0.465	0.173
Expanded farmland due to increasing demand for farmland resulting from a growing family size (1=yes, 0 otherwise)	0.56	0.502	0.29	0.458	0.006**
Household member(s) belonging to any formal or informal farmer group/ association (1=yes, 0 otherwise)	0.91	0.282	0.54	0.501	0.000**
Household member(s) received any form of agricultural extension training between the period 2015 - 2020 (1=yes, 0 otherwise)	0.86	0.345	0.50	0.502	0.000**

**Significant at 5%. Source: Authors. P-values refer to two-tailed t-tests

Endogenous Switching Regression Models Probit model estimates of SAI adoption. The empirical results for the probability of adopting SAI show significant and positive effects of a unit increase in total cropped area, farmer affiliation to farmer associations and farmer participation in agricultural extension training on sustainable agricultural intensification practices adoption. The estimation coefficient for agricultural farmland expansion variable is negative and significant at 95 percent confidence level. This finding implies that a unit increase in farmland expansion results in an 18.6 percent point decrease in the probability of a farmer to adopt SAI practices. Cropped land size, which is the main source of livelihood for farmers, has a positive and significant impact on the probability of adopting SAI practices. The marginal effects analysis show that a small unit increase in crop area cultivated from the mean led to a 0.03 percentage points increase in the probability of deciding to adopt SAI practices holding all other factors constant, a finding that is consistent with previous studies using farm size as a determinant of technology adoption (Akudugu, 2012; Nyariki, 2012).

The coefficient of farmer affiliation to farmer associations is also positive and significantly different from zero, suggesting that farmer groups play an important role in technology diffusion as supported by other studies (Norton *et al.*, 2020). A unit increase in farmer affiliation to farmer association increases the probability of SAI adoption by 31.9 percent holding all other factors constant. The agricultural extension training variable is positive and statistically significant in the probit model results, indicating that farmers with contacts to extension agents are more likely to adopt SAI practices. This result demonstrates the importance of knowledge in lowering ambiguity surrounding agricultural practices. The marginal effects analysis results indicate that a unit increase in agricultural extension training received by a farmer increases the probability of adopting SAI practices by 32.9 percent.

Table 2. Probit model estimates of SAI adoption

Variable	Coefficients	Marginal effects	Std. Err.
Household engaged in expansion of farmland Between 2015-2020 *	-0.471**(-2.44)	-0.186**	0.075
Household size	-0.028(-0.52)	-0.011	0.021
Number of household members between 16-59 years old	-0.089(-1.2)	-0.035	0.029
Education level	0.137(1.12)	0.054	0.048
Number of cattle owned*	-0.104(-0.51)	-0.041	0.080
Household ownership of a magoye ripper*	-0.065(-0.27)	-0.026	0.094
Total Cropped field	0.089**(2.12)	0.035**	0.017
Household member belonging to any formal or informal farm association*	0.827**(3.24)	0.320**	0.092
Household members received any form of agricultural extension training between 2015-2020*	0.850**(3.81)	0.329**	0.081
_cons	-0.985**(-2.31)		
Probit regression	Number of obs. = 246 Wald chi2(9) = 68.89 Prob > chi2 = 0.0000		

Notes: ** represents 5% significant level. Figures in parentheses are z-values.
(*) dy/dx is for discrete change of dummy variable from 0 to 1.

Table 3. Continuous switching regression results for the area under expansion for adopters and non-adopters without and after controlling for selection bias

Area under Expansion	Without controlling for selection bias		Adopters		Non-adopters	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Household size	0.031	0.036	0.031(-0.85)	0.043	-0.017(-0.27)	0.063
Age of household head	-0.034**	0.016	-0.010(-0.76)	0.013	-0.026(-1.63)	0.016
Years of farming	0.011	0.015	0.013(1.17)	0.011	-0.006(-0.30)	0.020
Level of Education	-0.396**	0.174	-0.119(-0.89	0.134	-0.454(-1.52)	0.298
Ownership of work oxen	0.152	0.217	-0.032(-0.25)	0.130	-0.560(-1.45)	0.387
Declining soil fertility	2.140**	0.598	0.979(1.42)	0.689	2.174*(2.57)	0.844

Some crop requirements for fertile new fields	1.055	0.579	3.324*(3.15)	1.055	0.884(1.39)	0.635
Higher fertiliser dosage for old fields	-0.586	0.614	-4.660*(-3.73)	1.251	0.154(0.22)	0.696
Non-adoption of alternative fertiliser sources	-1.887**	0.565	-3.616*(-6.35)	0.570	-1.549*(-2.16)	0.716
Limited cash to purchase fertilisers	2.001**	0.660	5.932*(7.58)	0.783	0.468(0.69)	0.681
Growing family size	2.001**	0.423	2.285*(4.42)	0.517	1.488(1.87)	0.794
Ease access to forest areas	1.011	0.801	-1.312(-1.27)	1.031	1.645*(2.57)	0.641
Farm size	0.063**	0.028	0.006(0.33)	0.017	0.292*(3.88)	0.075
Total land size cultivated	0.116	0.071	0.104(1.73)	0.060	0.263(1.48)	0.178
Age (years) of maize field	0.003	0.007	-0.0163*(-2.29)	0.007	0.023(1.68)	0.014
Household membership to farmer associations	0.353	0.276	1.284*(2.06)	0.622	0.729(0.90)	0.812
Participation in agricultural extension training	-0.272	0.280	0.964(1.47)	0.656	0.907(0.83)	1.094
m11			1.281(1.20)	1.067		
m00					1.542(0.92)	1.668
_cons	1.158**	0.608	-1.889(-1.16)	1.623	0.707(0.89)	0.797
R-squared	0.6752	0.8558				

Factors associated with smallholder farmland expansion. A comparison of the factors that influenced agricultural farmland expansion among adopter and non-adopter farm households was made using a continuous switching regression for the area under expansion while controlling for selection bias by including the inverse Mills ratio. The results in Table 3 indicate that declining soil fertility is an important factor that contributes to farmland agricultural expansion among non-adopters of SAI practices. The positive and significant coefficient of the variable suggests that non-adoption coupled with limited or lack of application of sustainable farming practices that increase or maintain soil fertility may increase the probability of farmer engagement in agricultural expansion.

The variable on some crop requirement for relatively new fertile fields shows a positive and significant coefficient among adopters of SAI practices. This result shows that the adopter farm households will increase the probability of expanding into new fields if they intend to grow a new crop that performs well in relatively new and fertile land. The results also show a negative and significant coefficient for the adopters for the higher fertilizer dosage requirement in the old fields variable. This implies that, as the field gets older, the adopters reduce the quantity of fertilizers they apply to the field either because the levels of soil fertility become stable or the fields do not decline to a level where they negatively impact crop production.

The variable on farmland expansion due to the lack of adoption of other sources of fertility improvement methods has a negative and significant coefficient for both adopter and non-adopter farm households. Therefore, the result indicates that the less access farmers have to other sources for fertility improvement, the higher the probability of them resorting to expanding their fields into virgin land. This is expected especially in view of the high cost of inputs particularly inorganic fertilisers that are beyond the reach of most farmers. Additionally, the coefficient for the variable on limited cash to purchase fertilisers is positive and significant for the adopters. This finding implies that despite a farmer's adoption of SAI practices, the more they face financial challenges to purchase inorganic fertilisers, the higher the chances that they will expand into new virgin land in order to maintain a higher crop productivity. The growing family size among the adopters, was another variable that show positive and significant impact on farmland expansion. Therefore, the bigger the family size, the higher the probability of resorting to expansion. The coefficient for easy access to forest areas among the non-adopter have the expected positive sign and is significantly different from zero, indicating that the closer a farmer is to the protected forest area, the higher the probability of them encroaching and opening up new land. On the other hand, the coefficient for the total farmland size owned variable is positive and significantly different from zero, suggesting that the larger the farm size, the higher the probability that a non-adopting farm household will expand. The coefficient for the age of the maize field among adopters was negative and significantly different from zero. This finding suggests that despite an increase in the age of the maize field, the probability of expanding the field reduces among the adopters. This result could be attributed to the application of sustainable agricultural practices that maintain soil fertility of the fields irrespective of the age hence reduces the chances of a SAI adopter farmer to open up new and virgin land. Participation in farmers' associations has a positive and significant impact on farmland expansion for adopters. This finding corroborates with Durlauf and Fafchamps (2005), who indicated in their study that social networks may be crucial in reducing search and information costs associated with the adoption of new technologies.

Treatment effect of SAI adoption on expansion. Table 4 shows the results of the expected land associated with expansion for adopters and non-adopters of SAI practices as well as their respective counterfactuals. The results revealed that the expected Food Consumption Scores (FCSs) of adopters and non-adopters were 53.87 and 66.92 respectively. Comparing (a) and (c) in Table 4 reveals that the adopters of SAI would have expanded land for agricultural practices by 0.61 hectares had they not adopted SAI practices. Therefore, the treatment, (i.e., adoption of SAI practices) reduced expected land expansion by 0.61 hectares. Comparing (b) and (d), non-adopters would have reduced land expansion by 0.88 hectares had they chosen to adopt SAI practices (significant at 1% level of significance).

Table 4. Treatment effect of SAI adoption on farmland expansion

Regime	Decision making regime		Treatment effect	T-Statistic
	Adopt	Not adopt		
Adopters	(a) 1.262397	(c) 1.876968	-0.61457	-2.1449
Non-adopters	(d) 1.273465	(b) 2.156383	-0.88292	-2.7896

DISCUSSION

The higher percentage of the farm households that received agricultural extension training and also involved in farmland expansion among adopters of SAI practices could be attributed to the need to expand production and increased farm income mainly as a result of enhanced agricultural productivity that results from improved farmer knowledge on farming practices through extension training. A similar study in Ghana by Danso-Abbeam (2018) also reported that participants in the Association of Church-based Development NGOs (ACDEP) agricultural extension programme had larger farm sizes than their non-participants counterparts. Members of such extension programmes are encouraged to consider their farms as a business entity rather than a cultural way of life and are, therefore, poised to achieve higher output through expansion and productivity.

The present findings showed that farmers with contacts to extension agents were more likely to adopt SAI practices. Agricultural extension, as previously noted, frequently serves as a significant information source on technological advancements in the agricultural sector in sub-Sahara Africa, and as such, can play a significant role in technology adoption. Our findings therefore collaborate those of other studies (Alene, 2006; Altalb, 2015) which indicated that agricultural extension is the basis for the transfer of agricultural technologies to farmers and to persuade farmers to adopt those agricultural techniques.

The negative relationship between the level of education of the farmer and farmland expansion, suggests that more-educated farmers are less likely to resort to expanding land under cultivation as an option to maintain productivity but instead find other more sustainable options. This result supports the idea that education is crucial for assisting farmers in making decisions regarding the adoption of new innovations and technology (Huffman, 2001).

The coefficient for increasing demand for farmland resulting from the growing family size variable is positive and significantly different from zero, suggesting that larger families will demand more land for cultivation to meet the household food needs as well as land for the other family members who may require to establish their own fields as they become socially and economically independent. This is perhaps not surprising, given the prominence of population in the broader review of the literature by Jellason (2021) which report that, population dynamic is a key underlying driver of agricultural expansion at both site and country levels. The coefficient for the total land size owned variable is positive and significantly different from zero. To augment this finding, Lawrence (2014) asserts that the global footprint of agriculture is likely to increase markedly this century as the global extent of cropland is currently expanding faster than at any time in the past 50 years and this will also be influenced by the total land owned at farm household level.

Findings from the study reveal that declining soil fertility is directly associated with an increase in the probability of farmer engagement in agricultural farmland expansion. This finding is in harmony with other studies (Chauvin, 2012; Epule, 2022) which indicate that in Sub-Sahara Africa, agriculture is marked by low productivity with little application of science and technology and farmers often resort to increasing the area under production by opening up of relatively fertile new forest fields in a bid to increase production. The limited financial resources among smallholder farm households has also been a push factor for agricultural farm expansion. Other researchers (Mwangi, 1996) indicate that Sub-Saharan Africa consumes very little fertilizer and needs policy help in the form of subsidies and credit to make the input more cheaper as they expand their crop area under production to satisfy the need for food security, corroborate this finding.

CONCLUSION

We estimated the causal effect of SAI practices adoption on agricultural farmland expansion among smallholder farm households in Katete district of Zambia. The study utilized endogenous switching regression and propensity score matching methods to assess the robustness of the results. This helped in estimating the true welfare effect of SAI practices adoption by controlling for the problem of selection bias. The causal impact estimation reveals that the adoption of SAI practices reduced expected land expansion on one hand while the non-adopters of SAI practices would have reduced land expansion had they chosen to adopt SAI practices. The findings also indicate that increasing area under cropping, farmer affiliation to farmer associations, and farmer participation in agricultural extension training are positive precursors to increasing the probability of adopting SAI practices at the farm level. Additionally, the more educated a farmer is coupled with older age reduces the probability of engaging in farmland expansion. These two variables point to the role and importance of increased farming experience and knowledge in mitigating the high rate of agricultural farmland expansion. This finding suggests that the mitigation of agricultural productivity challenges through technology dissemination should be coupled with farmer education. On the other hand, conventional factors of production such as limited cash to purchase fertilizers, increasing demand for farmland resulting from the growing family size, total land size owned, and the declining soil fertility, as expected, positively and significantly contributed to agricultural farmland expansion in an effort to maintain high crop productivity and production. The results from this study, therefore, generally confirm the potential positive impact of SAI technology adoption in reducing agricultural farmland expansion among smallholder farmers which translates into increased conservation of natural resources, especially forests.

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STATEMENT OF NO-CONFLICT OF INTEREST

The authors declare no conflict of interest in this paper.

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