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Responding to inefficiencies on smallholder maize farms: Can sustained adoption of sustainable agricultural practices make a difference?

Wisdom Richard Mgomezulu*
Lilongwe University of Agriculture and Natural Resources, Lilongwe, Malawi/Department of Law & Economics, Malawi University of Business and Applied Sciences, Blantyre, Malawi. E-mail: mgomezuluwisdom@yahoo.com

Kennedy Machira
Department of Agricultural Economics, Lilongwe University of Agriculture and Natural Resources, Lilongwe, Malawi. E-mail: kmachira@luanar.ac.mw

Abdi-Khalil Edriss
Department of Agricultural Economics, Lilongwe University of Agriculture and Natural Resources, Lilongwe, Malawi. E-mail: abdikhalil@yahoo.com

Innocent Pangapanga-Phiri
Department of Environmental Sciences, Lilongwe University of Agriculture and Natural Resources, Lilongwe, Malawi. E-mail: ipangapanga@luanar.ac.mw

Moses M.N. Chitete
Department of Sustainable Agriculture, University of Livingstonia, Mzuzu, Malawi. E-mail: mchitete@unilia.ac.mw

* Corresponding author

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Abstract

This study aimed to bring forth empirical evidence of the effect of the sustained adoption of sustainable agricultural practices (SAPs) on the technical and profit efficiency of farmers. Previous studies remain inconclusive about whether the adoption of SAPs has any bearing on the efficiency of maize farmers. The current study introduced the concept of sustained adoption and compared levels of efficiency between one-time SAP adopters and sustained adopters. Using a sample of 2 100 households, the study employed the Cobb-Douglas stochastic frontier model to analyse both the technical and profit efficiency of maize farmers, and a two-stage tobit model was used to control for endogeneity. The study found that the one-time adoption of SAPs has no effect on the technical efficiency of maize farmers, whilst sustained adoption significantly improves the technical and profit efficiency of maize farmers. The study recommends a shift towards promoting the sustained adoption of SAPs for sustainable benefits for farmers.

Key words: efficiency, Malawi, stochastic frontier, sustained adoption, sustainable agricultural practices

1. Introduction

The Global Hunger Index (GHI) report ranks Malawi in 87th position out of 121 countries included in the sample for the GHI calculation in 2022 (ReliefWeb 2022). The report shows that Malawi has an index score of 20.7, a level that is categorised as serious. Thus, attempts to boost agricultural production should be viewed as the only option to get Malawi out of the hunger and poverty trap (Goshu *et al*. 2013). As agricultural production is a key contributor to economic growth, it has witnessed a number of developments tailored at increasing the productivity and welfare of smallholder farmers. One of the prominent deployments is adoption of agricultural technologies and practices aimed at increasing yields in a climate-friendly manner.

Furthermore, the literature on climate change has shown that Sub-Saharan Africa (SSA) is one of the most affected regions, further establishing the need to promote the adoption of sustainable agricultural practices (SAPs) by smallholder farmers. For instance, the Intergovernmental Panel on Climate Change (IPCC) observed that temperatures increased by an average of 0.45 and 0.55 degrees between 2000 to 2010 and 2011 to 2020 respectively (IPCC 2022). The adverse impacts of climate variability and climate change, coupled with rising levels of poverty, have had an adverse effect on the adaptive capacity of households to respond positively to food insecurity-related shocks (Ayanlade *et al*. 2018; Adaawen *et al*. 2019; Uwizeyimana *et al*. 2019).

Researchers, governments and non-governmental organisations (NGOs) working with smallholder farmers in SSA have promoted the soil fertility management (SFM) approach for many years. The SFM involves combining the utilisation of mineral fertilisers, like urea or NPK, with the use of grain legumes, nitrogen-fixing plants, crop wastes and manure (Sauer & Tchale 2009; Krah *et al*. 2019). The World Bank (2018) defines SAPs as agricultural practices that ensure efficiency in the use of natural resources, whilst moderating the effects of agriculture on the environment, while at the same time improving the adaptive capacity of farmers to the adverse effects of climate change. These include conservation agriculture (CA) practices, like mulching, no tillage and intercropping or crop rotation; climate smart agriculture practices (CSA), like pit planting and water-harvesting technologies; and SFM practices, like organic manure and fertiliser tree technologies, among others. The adoption and upkeep of SAPs in SSA has featured highly in the development policy agenda (Mwalupaso *et al*. 2019).

Research on the effect of adopting SAPs on the productivity and efficiency of smallholder agriculture is growing (Adimassu *et al*. 2017; Ekman 2021; McCarthy *et al*. 2021; Mujeyi & Mudhara 2021; Pangapanga-Phiri & Mungatana 2021). Nonetheless, the evidence remains inconclusive. Pangapanga-Phiri and Mungatana (2021), for instance, noted an 18% improvement in technical efficiency for farmers adopting organic manure; Ekman (2021) found that intercropping and organic manure improve productivity by 59% and 54% respectively, whilst Mujeyi and Mudhara (2021) noted that the adoption of mulching, organic manure, crop rotation and intercropping improved profit efficiency. In contrast, Adimassu *et al*. (2017) found that the adoption of SAPs, including stone bunds, significantly reduced maize yields. Furthermore, McCarthy *et al*. (2021) noted that minimum tillage, mulching and vetiver grass did not improve the productivity of Malawian smallholder farmers. Other scholars have also found technical and profit efficiency of smallholder farmers to be affected by socioeconomic factors, rather than by the adoption of SAPs (Musa *et al*. 2015; Mapemba *et al*. 2019).

In the current study, we note that the adoption of SAPs is affected most by the unsustainable implementation of these approaches. For instance, Bell *et al*. (2018) point out that the benefits of climate resilient practices like mulching, no tillage and intercropping can only be realised from the consistent adoption of the technology. On the other hand, there is an emerging literature proposing the assessment of agricultural interventions two years after adoption in order to capture noticeable effects (De Brauw *et al*. 2019; Vaiknoras *et al*. 2019; Amadu *et al*. 2020). Furthermore, Bell *et al*. (2018) note that farmers tend to reduce the acreage of land under the practice over time and still report to have adopted SAPs. To that extent, past studies that have modelled SAPs have overlooked these two key aspects in their focus on adoption in a one-time survey period, hence the inconclusive findings (Adimassu *et al*. 2017; Ekman 2021; McCarthy *et al*. 2021; Mujeyi & Mudhara 2021; Pangapanga-Phiri & Mungatana 2021).

In the current study, we estimated the effect of sustained adoption of SAPs (mulching, organic manure and pit planting) on technical and profit efficiency. The three practices were considered because this study collected data in the climate shock-hit areas of Malawi under the Sustainable Food Systems in Malawi (FoodMa) programme, in which these practices are promoted. Different practices were initially considered in the mix, but their adoption rates were too negligible (< 1%) to be considered for modelling. We define sustained adoption in two ways: (1) a farmer is defined to have adopted the SAPs sustainably if they were practised consistently for the previous three years (Ruel *et al*. 2018; De Brauw *et al*. 2019; Dillon *et al*. 2019; Vaiknoras *et al*. 2019; Amadu *et al*. 2020); and (2) following Bell *et al*. (2018), the farmers' acreage of land under the practice was not reduced in the three years of consistent adoption. This provides room to effectively assess the effect of SAPs on the efficiency of smallholder farms, as it avoids categorising farmers who adopted in the current survey season but had not in the previous few seasons, and those who practised on a smaller portion of land and left the other portion under conventional farming, as adopters of SAPs. Nonetheless, we note that some farmers also expand the amount of land under the practice, which we checked for in the data and noted no significant adjustments in the three years. This is basically due to the small landholding sizes in the country (World Bank 2020). However, even if such cases existed, such farmers would still be considered sustained adopters, as the initial amount of land under the practice was not traded off for conventional farming (Bell *et al*. 2018).

Through testing the null hypothesis that both one-time survey season adoption and sustained adoption of SAPs do not improve smallholder farmers' technical and profit efficiency, the study notes that there is a need for a shift towards promoting the sustained adoption of SAPs. As such, the current study adds to the existing literature in two ways. First, it adds to the growing and yet small literature on SAPs by providing a shift in policy direction not only towards how to assess the adoption of SAPs, but also on how to refine extension messages for sustainable benefits for smallholder farmers. Lastly, it provides a novel evidence base for the scalability of SAPs amidst the current debates on low levels of technical efficiency (or productivity) and low adoption rates of SAPs resulting from the inconsistent uptake of agricultural technologies.

2. Methodology

2.1 Theoretical framework

2.1.1 The Cobb-Douglas theorem

We based the theoretical underpinnings of this study on the Cobb-Douglas theorem. Tijani *et al*. (2013) note that the theorem presents an economic theoretical analysis of the price-quantity path, with quantity and price assumed to be linked in a causal chain, i.e. with higher prices stimulating production in the next year, and vice versa. Equation (1) represents the cobweb model as follows:

$$Q_t^s = f_1(P_{t-1}) + e_t \qquad t = 1,\dots, n, \tag{1}$$

where Q_t^s is the current quantity produced, which is dependent on the past season price function, $f_1(P_{t-1})$, and e_t is the error term. Furthermore, the theorem assumes that all smallholder farmers are rational, and hence the study assumes that farmers adopting SAPs are producing efficiently. The study hence presents the model as stochastic, as observations are considered to be inefficient (Mapemba *et al*. 2019).

$$\Pi i = f(P_i Z_i \beta_i) E_i, \tag{2}$$

where Πi is the normalised profit obtained from produce under SAPs; P_i is the normalised price of inputs of production; Z_i represents the factors of production on the farm, i.e. fertiliser, labour and pesticides; β_i represents a vector of parameters; and E_i represents the stochastic error term split into v and μ:

$$E_i = v_i + \mu_i, \tag{3}$$

where v_i is strongly presumed to be an independent and identically distributed random error term that follows a normal distribution, $N\ (0,\ \sigma^2)$. Again, u_i is a one-sided error, which represents profit inefficiency, and also is a non-negative truncation of the half normal distribution, $N(u,\ \sigma^2 u)$.

2.1.2 The cost minimisation theorem

Next, the study follows Debertin (2004), who presented the cost minimisation problem, which comprises two factors in relation to profit maximisation. Thus, farmers can either maximise profits, or minimise the cost of producing the profit-maximising quantity. In this scenario, farmers adopting SAPs can thus minimise the costs of production, subject to the constraint that revenue is a fixed amount. Following Varian (1984), and further assuming the presence of competitive output and input markets, the cost minimisation problem is presented as follows:

$$Min\ C = \sum_n \omega_n x_n \tag{4}$$

$$st \quad Y_k^{i*} = A \prod_n x_n \beta_n, \tag{5}$$

where

$$A = \exp\ (\beta_0). \tag{6}$$

In the above, C is the total production cost; ω_n is a vector of input prices; x_n is a vector of inputs of production, such as labour, fertiliser, herbicides, pesticides and seeds; β represents parameter estimates; and Y_k^{i*} is the maize output adjusted for the given input levels.

Following Varian (1984), we present the dual cost function as follows:

$$C\left(Y_k^{i*}, \omega\right) = H Y_k^{i*\mu} \prod_n \omega_n^{x_n} \tag{7}$$

for

$$\alpha_n = \mu \beta_n, \tag{8}$$

$$\mu = \left(\sum_n \beta_n\right)^{-1} \tag{9}$$

and $H = \frac{1}{\mu}\left(A \prod_n {\beta_n}^{\beta_n}\right)^{-\mu}$. (10)

Since the farmer maximises profits by minimising costs, applying Shepard's lemma to Equation (7), and further making a substitution of the price of inputs and the maize output level that has been adjusted for inputs, gives rise to the following demand function:

$$\frac{\alpha C_i}{\alpha \omega_n} = X_i^e(\omega_i, Y_i^*, \theta), \tag{11}$$

where θ is a vector of the parameters of the array of inputs. As such, the observed, technical and economically efficient input vectors of farmer i can be given $\omega_i' X_i$, $\omega_i' X_i^t$ and $\omega_i X_i^t$ respectively. Hence, the technical and economic efficiency of the farmer from the cost minimisation problem can be presented as follows:

$$TE_i = \frac{\omega_i' X_i^t}{\omega_i' X_i}, \text{ and} \tag{12}$$

$$EE_i = \frac{\omega\prime X_i^t}{\omega_i' X_i}, \tag{13}$$

where ω' and ω_i' represent the vectors of observed and efficient input prices respectively; and X_i and $X\_i\hat{}t$ represent the vectors of observed and efficient inputs respectively. The constrained problem represents the production technology as:

$$y = g(x, A), \tag{14}$$

where x represents the inputs of production, A provides the technology used, and y is the output. We further assume that the technology, $g(x, A)$, is strictly decreasing and concave in x (Varian 1984). Furthermore, in the absence of technical change, $A\_t = 1$ for t = 1, 2…., T, then $g(x\_t, 1) = 0$. This explains the weak axiom of profit maximisation. Thus, if the farmer maximises profit given ω_t, then $\omega_i' X_i^t$ should be greater than or equal to the profits generated by any other set of outputs and inputs evaluated at ω_t. For cost minimisation, the input X_t minimises the cost over all choices that can at least produce y.

2.2 Analytical framework

2.2.1 The stochastic production frontier model

The current study notes that different studies have used the stochastic production frontier model (Chirwa 2007; Musa *et al*. 2015; Belete 2020) to measure efficiency. Methods for measuring efficiency can be grouped into parametric and non-parametric. Non-parametric production frontier measures differ from parametric frontier measures as they do not impose any functional form, and neither do they assume any distribution form of the disturbance term. In addition, we note that frontiers can be either deterministic or stochastic (Coelli *et al*. 1998). A deterministic frontier assumes that all the deviations from the frontier emanate from the inefficiency of the farm. On the other hand, a stochastic frontier assumes that part of the deviations emanate from a random component. Following Debertin (2004), the study employed a Cobb-Douglas production function and further specified a stochastic production frontier as follows:

$$\ln(y_i) = f(x_i, \beta) + \varepsilon_i, \tag{15}$$

where y_i is output; x_i is a vector of input i; and ε_i is a composite stochastic disturbance term such that $\varepsilon_j = v_j + \mu_j$. Different assumptions govern the distribution of the errors v_j and μ_j. Thus, μ_j is two-sided, whilst v_j is a one-sided error term. The systematic component, v_j, is assumed to be random and identically and independently (independent of μ_j) normally distributed. According to Coelli *et al*. (1998), the random systematic component explains the variations in the economic environment in which production operates. The inefficiency component of the frontier is provided by μ_j. According to Lee and Tylor (1978), the distribution of the inefficient component of the production frontier can take on many forms, but it is never symmetric.

Following Battese and Coelli's (1995) parameterisation, the inefficiency in the stochastic frontier was estimated using maximum likelihood, as presented by the following log likelihood:

$$\ln L = \frac{N}{2} ln\left[\frac{\pi}{2}\right] - \frac{N}{2} ln\sigma^2 + \sum_{j-1}^{N} ln\left[1 - F\left[\frac{\varepsilon_j\sqrt{\gamma}}{\sigma\sqrt{1-\gamma}}\right]\right] - \frac{1}{2\sigma^2}\sum_{j-1}^{N}\varepsilon_j^2, \tag{16}$$

where ε is the stochastic error component produced from the maximum likelihood estimation procedure presented by L; N is the total number of maize farms; F follows a normal distribution function; $\sigma^2 = \sigma_\mu^2 + \sigma_v^2$; and $\gamma = \sigma_\mu^2/\sigma^2$. Furthermore, and following the earlier work of Battese and Coelli (1995), the current study assumes a half-normal distribution of the inefficiency component μ_j, hence the mean or average technical efficiency of smallholder maize farmers practising SAPs can be presented as follows:

$$E\left[\exp\left(-\mu_j\right)\right] = 2\left[\exp\left(-\frac{\gamma\sigma^2}{2}\right)\right]\left[1 - F(\sigma\sqrt{\gamma})\right]. \tag{17}$$

What is crucial from the standard normal distribution of the maximum likelihood function is the estimation of the non-negative stochastic error term, μ_j, which measures the technical inefficiency in the frontier. Following Coelli *et al*. (1998), the current study presents the sources of inefficiency as follows:

$$ln\, y_{ij} = \varphi + \sum_{i=1}^{j}\beta \ln x_{ij} + \sum_{k=1}^{k}\theta SAPs_{kj} + \sum_{i=1}^{j}\omega AE_{ij} + v_j - \mu_j, \tag{18}$$

for

$$\mu_j = \delta_0 + \sum_{j=1}^{n}\delta_j z_j + w_j, \tag{19}$$

where, for farm i adopting SAP j, y_{ij} is the total quantity or production of maize in kilograms; xx_{ij} is a vector of inputs of production including land, labour, quantity of seed and quantity of fertiliser; *SAPs* represents dummies of organic manure, mulching and pit planting compared to the base of conventional farming; AE is a vector of agroecological factors including rainfall data and soil quality features; w_j are the unobservable random covariates that are assumed to be independently distributed after a truncation of the normal distribution, i.e. $N(0, \sigma_w^2)$; and μ_j represents the technical inefficiency estimates predicted simultaneously with the sources of inefficiency.

2.2.2 The stochastic profit efficiency model

Following the earlier work of Coelli *et al*. (1998), a similar approach as that for estimating technical efficiency was adopted to estimate economic efficiency. The individual farm-specific profit efficiencies were predicted from the stochastic production frontier model, as specified by the Cobb-Douglas model. The estimation of technical efficiency used the natural logs of quantities of inputs of production, whilst the economic efficiency estimation used the natural logs of the value of the inputs of production. As such, the economic inefficiency of the farms was predicted through a stochastic frontier analysis (SFA) approach (Battese & Coelli 1995; Coelli *et al*. 1998). The model can be represented as follows:

$$ln\pi_i = \beta_0 + \beta_1 lnLabcost + \beta_2 \ln Seedcost + \beta_3 lnFertcost + \beta_4 lnPestcost + (v - \mu), \qquad (20)$$

where $ln\pi_i$ is the restricted normalised profit of smallholder maize farmers (MK per ha); $lnLabcost$ is the costs of labour normalised by price of maize (MK per man day of labour); ln $Seedcost$ is the cost of maize seed normalised by price of maize (MK per kg of seed), $lnFertcost$ is the cost of fertiliser normalised by price of maize (MK per kg of fertiliser); $lnPestcost$ is the cost of pesticides normalised by price of maize (MK per litre of pesticide); β_0 to β_4 are parameters to be estimated; v is the symmetric component of the white noise that depicts factors outside the control of the farmer; and μ is the non-negative random variable under the control of smallholder maize farmers that depicts the economic inefficiencies.

2.2.3 The two-stage censored tobit model

The study employed a two-stage tobit model to analyse the effect of SAPs (mulching, pit planting and organic manure) on the efficiency of farmers. A probit model was employed in the first stage to estimate factors affecting the adoption of the SAPs. The predicted scores were then included in the tobit model to solve for endogeneity bias in assessing the influence of adopting SAPs on efficiency. The popular OLS used by many authors, such as Chirwa (2007) and Musa *et al*. (2015) in the analysis of determinants of inefficiency was not applicable, since the inefficiency scores ranged from 0 to 1. This follows a double truncation with a lower and upper limit, violating the normal distribution assumption of the OLS (Wooldridge 2015).

The probit model can be represented as

$$P_{ijt} = \delta_0 + \sum_{j=0}^{j} \delta_j Z_j + w_j \qquad \text{for t = 1, 2, 3,} \qquad (21)$$

where P_{ijt} takes a value of one if a farmer adopts a particular SAP (i.e. mulching, organic manure or pit planting) for the three years, and zero otherwise. δ_0 is a constant term, Z_j is a vector of explanatory variables, whilst δ_j represents parameters to be estimated and w_j is the error term.

Following Tobin (1958), the inefficiency predicted from the stochastic frontiers can best be presented as a latent variable-specification problem:

$$\mu_j^* = \delta_0 + \sum \delta_j Z_j + \; + \gamma_j \, \mathrm{M_{ijt}} \; + w_j, \qquad (22)$$

where μ_j^* is the latent variable indexing inefficiency (technical or profit) of the farm; δ_j is a vector of unknown parameters to be estimated; Z_j is a vector of explanatory variables (socioeconomic, institutional, agroecological and farm-level factors); $\mathrm{M_{ijt}}$ is a vector of predicted values of mulching, pit planting and organic manure from Equation (21); and w_j is the error term that is independent and normally distributed, i.e. $N(0, \sigma_w^2)$.

The observed variables of the technical efficiencies can be represented as follows:

$$\mu_j = \begin{cases} 1 & if\ \mu_j^* \geq 1 \\ \mu_j^* & if\ 0 < \mu_j^* < 1, \\ 0 & if\ \mu_j^* \leq 0 \end{cases} \qquad (23)$$

where μ_j denotes the observed technical efficiency on farm j, whilst μ_j^* represents a latent variable indexing the observed technical efficiencies on farm j.

2.3 Diagnostic test

In order to ascertain the relevance of using a stochastic frontier over a normal linear model, log likelihood tests were performed, as recommended by Kumbhakar *et al*. (2015). The two models differ because stochastic models assume that the error term is composite and comprises variance coming from both the inefficient component and that coming from the random component. The likelihood ratio compares the restricted model (see Table A2 and A3 in the Appendix) with an unrestricted model's log likelihood ratios using the following formula:

$$\lambda = -2[L(H_0) - L(H_1)], \tag{24}$$

where $L(H_0)$ and $L(H_1)$ represent the log-likelihood values computed from the restricted OLS model and the unrestricted stochastic frontier models respectively. The computed statistic was then compared to critical values, of which the results show that the stochastic frontier was justified.

2.4 The data

The study was conducted in 349 randomly sampled enumeration areas (EAs) in the three districts of Mzimba, Kasungu and Mchinji (see Table A1 in the Appendix). A total of 2 100 farming households were sampled systematically through proportional sampling to the size of the districts, hence using sampling weights. Sample weights were calculated as the inverse of sampling probabilities at each sampling stage. Considering that the sampling of climate variability-prone areas was done by the FoodMa project, the study only calculated sample weights for the remaining two sampling stages, viz. sampling for EAs and farming households. The probability of sampling EAs, f_{1i}, was calculated as below:

$$f_{1i} = \frac{a_i * n_i}{c_i}, \tag{25}$$

where a_i is the number of EAs to be sampled in a district, n_i is the number of households in a sampled EA, and i and c_i are the total number of households in a district to which an EA belongs. The probability of sampling a farming household, f_{2i}, was calculated as indicated below:

$$f_{2i} = \frac{b_i}{n_i} \tag{26}$$

The sampling weight, sw_i, was calculated as below:

$$sw_i = \frac{1}{f_{1i} * f_{2i}}, \tag{27}$$

where b_i is the number of sampled households in the sampled EA, and i and n_i are the total number of households in an EA. The inverse of the product of the two probabilities, as presented in Equation (27), constitutes the final sample weight attached to each sampled household.

Qualitative data (focus group discussions and key informant interviews with extension workers) collected from the EAs were used to supplement the findings. Again, the study included three-year average rainfall and temperature data from CEDA (the Center for Environmental Analysis), and further controlled for soil type and perception of soil quality, which were crucial determinants of SAPs (Bachewe *et al*. 2015). These elements form part of the agroecological factors. Average monthly rainfall and temperature data for the preceding three years covering the sampled districts and enumeration areas were hence requested. Following Dessy *et al*. (2020), the study merged farmer characteristics with the computed average rainfall and temperature data from CEDA using the collected GPS coordinates. Table 1 provides a summary of the descriptive statistics of the surveyed farmers. The average number of members per household was around 4.4 to 4.7 persons. Household heads spent about 5.7 to 7.4 effective years in school, and most of them were aged from 43 to 47 years. The average land sizes were around 3.2 and 3.5 acres. With regard to the agroecological conditions, average temperature for the three years was around 21°C, whilst the three-year average precipitation was around 80.6 to 81.6 mm. The average maize output per hectare was 1 767 kg, whilst the average quantity of seed applied per hectare was 210 kg. The use of chemical fertiliser and pesticides amounted to 112.80 kg and 91.78 kg respectively. Labourers spent fewer than two hours working in their fields on average per day.

Table 1: Descriptive statistics of surveyed farmers

Variable	**Measurement**	**One-time adoption**	**Sustained adoption**	**One-time adoption**	**Sustained adoption**	**One-time adoption**	**Sustained adoption**
		Organic manure n = 935	Organic manure n = 818	Mulching n = 668	Mulching n = 498	Pit planting n = 244	Pit planting n = 154
HH size	Persons	4.5 (1.78)	4.49 (1.76)	4.4 (1.59)	4.4 (1.58)	4.6 (1.50)	4.7 (1.53)
HH education	Effective years spent in school	7.4 (3.4)	7.3 (3.5)	6.6 (4.1)	6.5 (4.05)	5.8 (4.1)	5.7 (4.2)
HH age	Years	43.3 (13.6)	43.5 (13.9)	44.4 (13.7)	44.5 (12.7)	44.7 (14.9)	45.7 (14.6)
Land size	Acre	3.3 (2.9)	3.2 (2.9)	3.4 (3.06)	3.3 (3.0)	3.5 (5.1)	3.4 (4.7)
Tropical livestock units (TLU)	Number	0.59 (1.35)	0.59 (1.4)	0.66* (1.48)	0.62 (1.42)	0.68* (1.6)	0.63 (1.5)
Three-year average temperature	Degrees Celsius	21.1 (0.96)	21.1 (0.96)	20.9 (1.04)	21.0 (1.03)	20.9 (1.1)	21.0 (1.1)
Three-year average rainfall	mm	80.7 (5.59)	80.8 (5.62)	80.6 (5.7)	80.7 (5.7)	81.2 (6.1)	81.6 (6.1)
Number of children in HH	Number	0.41 (0.58)	0.42 (0.58)	0.39 (0.57)	0.39 (0.57)	0.35 (0.54)	0.34 (0.54)
Soil type (%)	Sandy	11.08	11.76	14.09	13.78	21.16	18.53
	Loam	34.09	32.57	45.84	45.67	39.15	38.79
	Sandy loam	47.79	48.37	31.41	32.20	35.45*	38.36
	Clay	7.03	7.30	8.66	8.36	4.23	4.31
Perception of soil fertility (%)	Poor	12.04	12.64	27.84	28.33	38.10	37.93
	Fair	68.18	68.41	52.80	52.94	43.92	44.83
	Good	19.79	18.95	19.35	18.73	17.99	17.24
HH sex	Male (1/0)	0.822 (0.39)	0.818 (0.39)	0.817 (0.39)	0.815 (0.38)	0.823* (0.40)	0.807 (0.36)
Off-farm income activities	Yes (1/0)	0.027 (0.16)	0.027 (0.15)	0.019 (0.15)	0.022 (0.15)	0.01* (0.06)	0.004 (0.08)
Radio ownership	Yes (1/0)	0.246 (0.42)	0.233 (0.43)	0.202 (0.39)	0.191 (0.42)	0.196 (0.40)	0.192 (0.42)
Smartphone ownership	Yes (1/0)	0.034 (0.19)	0.037 (0.18)	0.023 (0.14)	0.020 (0.17)	0.005 (0.13)	0.016 (0.11)
Floods in past three years	Yes (1/0)	0.075 (0.26)	0.073 (0.27)	0.039 (0.19)	0.037 (0.21)	0.035 (0.19)	0.036 (0.21)
Dry spell in past three years	Yes (1/0)	0.722 (0.45)	0.713 (0.46)	0.845 (0.37)	0.841 (0.37)	0.808 (0.40)	0.795 (0.42)

Variable	**Measurement**	**One-time adoption** Organic manure n = 935	**Sustained adoption** Organic manure n = 818	**One-time adoption** Mulching n = 668	**Sustained adoption** Mulching n = 498	**One-time adoption** Pit planting n = 244	**Sustained adoption** Pit planting n = 154
Savings group membership	Yes (1/0)	0.271 (0.44)	0.260 (0.43)	0.281 (0.44)	0.260 (0.47)	0.196 (0.38)	0.176 (0.44)
Farmer club membership	Yes (1/0)	0.514 (0.50)	0.497 (0.50)	0.565 (0.50)	0.538 (0.48)	0.479 (0.50)	0.438 (0.50)
Attended SAPs field demonstrations	Yes (1/0)	0.807 (0.40)	0.793 (0.39)	0.882 (0.33)	0.877 (0.33)	0.904 (0.31)	0.893 (0.33)
Listened to SAPs radio programme	Yes (1/0)	0.832 (0.38)	0.825 (0.39)	0.930 (0.27)	0.919 (0.28)	0.954 (0.24)	0.938 (0.24)
Received SAPs training	Yes (1/0)	0.798 (0.41)	0.786 (0.40)	0.850 (0.36)	0.842 (0.38)	0.898 (0.32)	0.885 (0.34)
Extension visit in last 12 months	Yes (1/0)	0.704 (0.46)	0.687 (0.43)	0.759 (0.42)	0.752 (0.41)	0.813 (0.40)	0.790 (0.39)
Maize Yield	kg/ha	1 949.125 (357.79)	1 913.892 (344.91)	2 349.40 (406.2)	2 265.29 (390.91)	1 845.341 (126.64)	1 811.215 (126.44)
Fertiliser	kg/ha	115.554 (15.08)	116.497 (18.64)	135.67 (11.63)	134.874 (14.05)	118.66 (12.74)	117.03 (11.54)
Seed	kg/ha	24.73 (5.4)	24.83 (5.1)	21.98 (4.2)	21.90 (4.6)	20.58 (4.8)	20.54 (4.6)
Pesticides	kg/ha	66.11 (16.89)	66.11 (15.89)	168.5 (17.35)	145.5 (16.77)	211.2 (14.44)	211.2 (14.34)
Total labour	Hours/day	1.38 (0.64)	1.39 (0.6)	1.61 (0.83)	1.61 (0.82)	1.39 (0.69)	1.38 (0.67)

Notes: Standard deviation in parentheses; * $p < 0.1$

3. Results and discussion

3.1 Efficiency of maize farmers

First, the study estimated the technical efficiency of maize farmers adopting mulching, pit planting and organic manure. The stochastic frontier models were estimated for both one-time survey season adoption and sustained adoption. The overall average technical and profit efficiency of farmers was 66% and 55% respectively, implying that maize farmers in the study areas remain inefficient. Thus, farmers could reduce the inputs used proportionally by about 34% to achieve the same level of output. Similarly, farmers could reduce the cost of inputs by 45% to achieve the same level of profit. The technical efficiency of sustained organic manure adoption (69%) was significantly higher than the one-time adoption of organic manure (64%). The findings do not deviate much from those of other Malawian scholars, who also found inefficiencies in smallholder maize farms. For instance, Tchale (2009) found a mean technical efficiency score of 53%. Pangapanga-Phiri and Mungatana (2021) found a mean technical efficiency of 63%. This shows the need to improve the technical efficiency of smallholder maize farms. Likewise, the profit efficiency of sustained pit planting (64%) and sustained mulching (59%) was significantly higher than that of one-time adoption. Thus, despite the technical and profit efficiency scores of the smallholder farmers being expectedly lower, the efficiency scores for sustained adoption were on average significantly higher than those of one-time adoption.

Table 2: Summary of efficiency measures

Efficiency scores	Mulching		Pit planting		Organic		Pooled
	One time	Sustained	One time	Sustained	One time	Sustained	
Technical	0.65	0.67	0.66	0.67	0.64	0.69**	0.66
Profit	0.54	0.59*	0.57	0.64**	0.54	0.56	0.55

Notes: ** $p < 0.05$, * $p < 0.1$

Furthermore, the study notes that, from the overall (pooled) Cobb-Douglas model, fertiliser, seed, labour and land size were significant and positive determinants of productivity. For instance, a percentage increase in fertiliser application increased productivity by 18.7%; a percentage increase in quantity of seed increased productivity by 36.8%; a percentage increase in labour days increased productivity by 22.1%; and a percentage increase in land size increased productivity by 48.7%. Since land size was the reported harvested land, farmers with larger land sizes were able to benefit from economies of scale. In Malawi, the productivity of smallholder maize farmers remains low compared to the productivity on estate farms (Anti-Corruption Bureau 2021). This is why considerable resources are allocated to the Affordable Inputs Programme (AIP) to improve the productivity of smallholder farmers. Furthermore, focus group discussions revealed that farmers were not applying the recommended rates of inputs due to financial constraints. This explains the inefficiency, and why any increase in these inputs increases the maize yield. As such, the adoption of SAPs provides farmers with opportunities to improve soil health and fertility amidst low input use. Nonetheless, a positive and significant relationship also holds for each of the SAPs being adopted. This suggest that the use of the required inputs should again go hand in hand with the adoption of SAPs.

Table 3: Estimates of the Cobb-Douglas production function

Yields/ha	Mulching		Pit planting		Organic		Pooled
	One time	Consistent	One time	Consistent	One time	Consistent	
Lnfertiliser	0.189*** (0.009)	0.179*** (0.010)	0 .189*** (0 .009)	0.1786*** (0.010)	0 .188*** (0.009)	0.188*** (.009)	0.187*** (0.009)
Lnseed	0.395*** (0.035)	0.378*** (0.038)	0 .395*** (0 .035)	0.347** (0.038)	0.395*** (0 .035)	0.395*** (.035)	0.368*** (0.037)
Lnpesticides	-0.042*** (0 .041)	-0.041*** (0.045)	-0.042*** (0 .041)	-0.044*** (0.045)	-0.042*** (0.041)	-0.042 (.041)	-0.040 (0.041)
Lnlabour	0.168*** (0.036)	0.221*** (0.038)	0.168*** (0.036)	0.221*** (0.038)	0.168*** (0.036)	0.221*** (0.038)	0.221*** (0.038)
lnLand size	0.284*** (0.051)	0.349*** (0.151)	0.194 (0.152)	0.849** (0.392)	0.481** (0.163)	0.346*** (0.142)	0.487*** (0.131)
Constant	5.329*** (0 .118)	5.962*** (0.252)	5.329*** (0.118)	5.962*** (.252)	5.329*** (0.118)	5.329** (0.118)	3.500** (0.147)
Usigma	3.606*** (0 .919)	-1.995*** (0.592)	3.606*** (0.919)	-1.995*** (0.592)	3.606*** (0.919)	3.606*** (0.919)	3.571*** (0.700)
Vsigma	-0.834 (0.048)	-0.716 (0.160)	-0.834 (0.048)	-0.716 (0.160)	-.834 (0.048)	-0.834*** (0.048)	-0.833*** (0.049)

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Furthermore, the study estimated the stochastic profit frontier function and used normalised gross margins as profits in the stochastic frontier model. The results are presented in Table 4. The results show that, contrary to the expectation, the addition costs of fertiliser and land increased the gross margins. On the other hand, additional labour costs reduced the farmer's gross margins. This can be explained by the fact that more fertiliser and more land entail more fertility and a larger production area respectively, such that farmers are able to produce more output, resulting in an increased surplus to sell.

Table 4: Estimates of the stochastic frontier function

Gross margins	Mulching		Pit planting		Organic manure		Pooled
	One time	Consistent	One time	Consistent	One time	Consistent	
Lnfertiliser costs	0.088 (0.009)	0.088 (0.009)	0.088 (0.009)	0.089*** (0.009)	0.088 (0.009)	0.088 (0.009)	0.089*** (0.009)
Lnland costs	0.441 (0.043)	0.441 (0.043)	0.441 (0.043)	0.441 (0.043)	0.441 (0.043)	0.441 (0.043)	0.444*** (0.043)
Lnlabour costs	-0.072 (0.041)	-0.072 (0.041)	-0.072 (0.041)	-0.072* (0.041)	-0.072 (0.041)	-0.072* (0.041)	-0.072* (0.041)
Ln pesticide costs	0.021 (0.038)	0.021 (0.038)	0.021 (0.038)	0.020 (0.038)	0.021 (0.038)	0.020 (0.038)	0.020 (0.038)
Constant	7.620 (0.558)	7.620 (0.558)	7.620 (0.558)	7.610 (0.558)	7.620 (0.558)	7.610 (0.558)	7.610 (0.558)
Usigma	0.180* (0.098)	0.180* (0.098)	0.180* (0.098)	0.180* (0.098)	0.180* (0.098)	0.180* (0.098)	0.180* (0.098)
Vsigma	-0.164** (0.074)	-0.164** (0.074)	-0.164** (0.074)	-0.164** (0.074)	-0.164** (0.074)	-0.164** (0.074)	-0.164** (0.074)
sigma_u	1.094*** (0.054)	1.094*** (0.054)	1.094*** (0.054)	1.094*** (0.054)	1.094*** (0.054)	1.094*** (0.054)	1.094*** (0.054)
sigma_v	0.921*** (0.034)	0.921*** (0.034)	0.921*** (0.034)	0.921*** (0.034)	0.921*** (0.034)	0.921*** (0.034)	0.921*** (0.034)
Lambda	1.188*** (0.078)	1.188*** (0.078)	1.188*** (0.078)	1.188*** (0.078)	1.188*** (0.078)	1.188*** (0.078)	1.188*** (0.078)

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.2 Determinants of technical and profit efficiency

The study further sought to establish factors that determine the technical as well as profit efficiencies of maize farmers. The effect of one-time and sustained adoption of mulching, pit planting and organic manure were evaluated through the use of a two-stage tobit model. A probit model was first used to predict the adoption values of mulching, pit planting and organic manure. The predicted values were regressors in the inefficiency model, along with other covariates in the tobit model. The results are summarised in Table 5. For technical efficiency, the study found that the one-time adoption of any of the SAPs, viz. mulching, no tillage and organic manure, had no significant influence on technical efficiency. Thus, the findings of this study agree with the findings of Adimassu *et al*. (2017) and McCarthy *et al*. (2021), who found no significant effect of the conventional one-time adoption decisions of similar sustainable agricultural production practices. This necessitates a modelling shift towards the sustainability of the practices to observe significant effects. For instance, allowing for measurement in the sustainability of the practices, the study finds that sustained adoption of mulching, no tillage and organic manure significantly increase the technical efficiency of farmers, i.e. reduces the inefficiency of smallholder maize farmers.

In terms of profit efficiency, the results show that the one-time adoption of organic manure improves profit efficiency, whilst the one-time adoption of the other SAPs (pit planting and mulching) had no effect on profit efficiency. Nonetheless, sustained adoption of organic manure and pit planting were found to significantly increase the profit efficiency of maize farmers. This further cements the need for a modelling shift in order to capture the sustainability effects of the practices. The study went further to also control for other covariates and noted that the age of the household head, household head education level, ownership of a smart phone, soil type, farmer club membership, membership of a savings group and average temperature were significant determinants of technical and profit efficiency.

Table 5: Determinants of technical and profit efficiency of smallholder maize farmers

Efficiency	Technical		Profit	
	One time	**Consistence**	**One time**	**Consistence**
Organic farming	-0.003 (0.039)	-0.177*** (0.061)	-0.767*** (0.294)	-0.564** (0.219)
Pit planting	-0.052 (0.051)	-0.106** (0.053)	-0.292 (0.194)	-0.329* 0.194
Mulching	0.004 (0.023)	-0.077** (0.035)	-0.092 (0.159)	0.018 (0.128)
HH size	-0.001 (0.005)	0.006 (0.005)	-0.005 (0.024)	-0.020 (0.023)
HH sex	-0.028 (0.036)	-0.019 (0.036)	-0.005 (0.137)	-0.010 (0.137)
HH age	-0.011*** (0.003)	-0.010*** (0.003)	0.004 (0.012)	0.005 (0.012)
Age^2	0.0001** (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)
HH education	-0.006** (0.003)	0.000 (0.003)	0.023* (0.014)	0.017 (0.012)
Radio	-0.003 (0.021)	0.005 (0.021)	-.0230 0.082	-0.074 (0.078)
Smart phone	0.0389 (0.047)	0.050*** (0.046)	-0.325* (0.189)	-0.246 (0.186)
Loam	0.003 (0.035)	0.025 (0.035)	0.358* (0.141)	0.289** (0.136)
Sandy loam	-0.058* (0.030)	-0.026 (0.029)	0.402*** (0.124)	0.356*** 0.112
Clay	-0.062* (0.037)	0.017 (0.044)	0.255 (0.166)	0.235 0.164
Floods	0.061* (0.035)	0.044 0.035	0.358** 0.145	0.329 (0.145)**
Dry	0.032 (0.023)	0.051 0.024	0.029 (0.107)	-0.069 (0.089)
Farmer club membership	0.044 (0.024)	0.078*** (0.028)	0.209* 0.108	0.173 (0.106)
SAPs radio programme	-0.041 (0.029)	0.002 (0.030)	0.113 0.135	0.070 (0.113)
SAPs field demonstrations	-0.007 (.023)	0.049 (0.029)	1.009 0.428	-0.098 0.108
Extension visit	.005 (.027)	0.011 (0.026)	-0.002 (0.102)	0.031 (0.010)
Land size in hectare	-.0009 (.0303)	0.016 (0.031)	0.019 (0.114)	0.014 (0.113)
Three-year average temperature	0.048*** (0.009)	0.041*** (0.010)	0.140*** 0.044	0.181*** 0.036
Three-year average rainfall	.001 (.001)	0.000 0.001	-0.004 0.006	-0.001 (0.006)
Savings group	-0.058* (0.031)	0.124* (0.065)	0.509* (0.279)	0.370 (0.235)
Constant	-0.396* (0.235)	-0.827*** (0.273)	-4.13*** (0.917)	-4.595*** 1.025

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4. Conclusions and recommendations

The main focus of the current study was the evaluation of the effects of adoption of SAPs on the technical and profit efficiency of maize farmers. The technical and profit efficiencies were evaluated using stochastic frontier models of the Cobb-Douglas form. The study used a two-stage censored tobit model to analyse the determinants of technical and profit efficiencies. The first stage involved the prediction of SAPs adoption values through a probit model in an effort to eliminate possible endogeneity. The predicted values of mulching, pit planting and organic manure adoption were then used as explanatory variables, together with other covariates in a tobit model. Building on past research, which presents inconclusive findings on the matter, the study brought in a new concept of sustained adoption and compared the effects with the conventional modelling of the one-time adoption of agricultural technologies in a season. To that effect, the current study examined the null hypothesis, which states that neither the initial adoption of SAPs during a survey season, nor ongoing SAPs adoption, will increase the technical and profit efficiency of smallholder farmers. The current study contributes to the growing but still sparse body of knowledge on SAPs by offering a policy direction change toward not only how to assess SAP adoption, but also toward improving extension messages for long-term benefits to smallholder farmers. In the light of recent discussions about low levels of technical efficiency (or productivity) and poor adoption rates of SAPs as a result of the uneven uptake of agricultural technologies, the study offers a fresh evidence base for the scalability of SAPs and SAPs adoption messages. The study found that the sustained adoption of mulching, pit planting and organic manure positively influences farmers' technical efficiency, and there is no effect of one-time adoption on technical efficiency. Likewise, profit efficiency was positively influenced by the sustained adoption of mulching and pit planting. However, the one-time adoption of mulching also influenced profit efficiency. The study concludes that a change needs to be made in order to encourage the long-term adoption of SAPs. The study therefore recommends a shift in modelling to a focus on the sustained adoption of these practices for improvements in productivity and profits. This should involve refining the extension messages to focus on sustainability and to inform farmers that the effects of adopting SAPs improve with time.

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Appendix

Table A1: Sample sizes proportional to size of districts

District	Number of EAs	Number of households (rural)	Average number of HHs/EA	Sampled EAs (pps)	SAP project areas	SAP non-project HHs	Final sample
Mzimba	865	188 802	131	144	432	432	864
Kasungu	799	166 032	208	133	399	399	798
Mchinji	438	130 437	298	73	219	219	438
Total	2 102	485 271	637	349	1 050	1 050	2 100

Note: pps = proportional probability sampling

Table A2: Restricted OLS profit efficiency model

Gross margins	Pooled
Lnfertiliser costs	0.084*** (0.011)
Lnland costs	0.463*** (0.055)
Lnlabour costs	-0.060* (0.048)
Ln pesticides costs	0.051 (0.047)
Constant	6.189 (0.688)
Deviance	3 471.38
Pearson	3 471.38
AIC	3.664
BIC	-77.11
Log likelihood	-2797

Notes: Standard errors in parentheses; AIC = Akaike information criterion; BIC = Bayesian information criterion; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Restricted OLS technical efficiency model

Gross margins	Pooled
Lnfertiliser quantity	0.144 (0.011)
Inseed quantity	-0.375 (0.029)
Ln pest	-0.000 (0.03)
Lnlabour	0.318 (0.04)
Lnlandsize	1.215 (0.131)
Constant	6.250 (0.092)
Deviance	1 814.24
Pearson	1 814.24
AIC	2.697
BIC	-14 204.21
Log likelihood	-2 826

Notes: Standard errors in parentheses; AIC = Akaike information criterion; BIC = Bayesian information criterion; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$