32nd International Conference of Agricultural Economists
2-7 August 2024 I New Delhi I India

Understanding Farmer Adoption Decisions of Sustainable Agricultural Practices under Varying Agro-ecological Conditions: A New Perspective

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Abstract

Different scholars have modelled the adoption of sustainable agricultural practices (SAPs) with a goal of improving farmer's adaptive capacity to climate change. Nonetheless, through the conventional way of defining adoption decisions as one-time survey decisions, many scholars have failed to understand inconsistencies in adoption decisions and dis-adoption of such practices. Through a survey of 2100 maize farming households, the current study employed multivariate probit models to understand and compare one-time survey season adoption decisions and sustained (consistent) adoption decisions. The study notes that dis-adoption rates of SAPs range from 20 to 27 percent. As such, the determinants of dis-adoption were estimated to build a case for going beyond one-time adoption survey decisions. Furthermore, the study employed a Cox Proportional hazard model to understand the relative risk to adoption of Sustainable Agricultural Practices over time. The findings reveal the need for a modelling paradigm shift in understanding adoption decisions for sustainable benefits. Lastly, the findings reveal the need for intensifying knowledge and information dissemination on SAPs through field demonstrations, extension visits, trainings and radio programs in order to reduce dis-adoption and ensure sustained adoption.

JEL Codes: B21, B23, C41, Q50

1. Introduction

Adoption of Sustainable Agricultural Practices (SAPs) has overtime presented smallholder farmers with a better adaptive capacity to climate change. Sustainable Agricultural Practices can be defined as agricultural practices that warrant efficiency in the usage of natural resources, at the same time mitigating the impacts of agriculture on its environment whilst supporting farmers adaptive capacity to climate change (World Bank, 2020). These include Conservation Agriculture (CA) practices like mulching, no tillage, crop rotation and intercropping and other Climate Smart Agriculture (CSA) practices like pit planting, use of organic manure, agroforestry, water harvesting, erosion control bunds among others (Kurgat et al., 2020). Different scholars have studied how climate change has affected the Sub-Saharan Africa (SSA) region (Midgley et al., 2011); (Warnatzsch and Reay, 2015); and (Niang et al., 2014). Serdeczny et al. (2016) noted that rising temperatures, rising sea levels of above one meter and rainfall anomalies have over the past decade increased the occurrence and concentration of natural disasters. It is estimated that at warming levels of about 2 degrees Celsius above pre-industrial levels, SSA will experience 27-32% yield loss for maize, sorghum, millet and groundnut by mid-century (Niang et al., 2014).

Numerous scholars have studied the adoption of SAPs. For instance, in Tanzania, Kurgat et al. (2020) studied the determinants of adoption of CSA among smallholder farmers and focused on one-time adoption decision. Similarly, in Nigeria, Oyawole et al. (2019) studied the drivers of adoption of climate smart agricultural practices (use of green manure, agroforestry, organic manure, refuse retention, crop rotation and zero/minimum tillage) and employed models for one-time adoption decisions.

Whether through utilizing a cross-sectional or longitudinal dataset, past studies on adoption of SAPs have captured a single season adoption decision, disregarding inconsistency due to dis-adoption (and re-adoption) and whether farmers are able to maintain adoption intensity on the acreage of land. Bell et al. (2018) pointed out that the benefits of CA which include improving soil health and yields can only be realized from consistent adoption of the technology. The study further revealed that farmers fail to maintain the amount of land under the practice as the modern technologies are deemed to be tedious or cost consuming. Recent studies have argued that agricultural technologies need to be assessed at least two-years post intervention as benefits cannot be realized with one-time adoption (Wade and Claassen, 2017; de Brauw et al., 2019; Vaiknoras et al., 2019; Amadu et al., 2020a, Amadu et al., 2020b; Dillon et al., 2020). This mirrors adoption of SAPs as the benefits for example of agroforestry, organic manure, crop rotation/intercropping are mostly realized two or more seasons later (Bell et al., 2018). In the current study, we define sustained adoption in two dimensions: (1) a farmer is considered to have sustainably adopted the technology if practiced consistently for the past 3 years (De Brauw et al., (2019); Vaiknoras et al., (2019); Amadu et al., (2020); Ruel et al., (2018); Dillon et al., (2019)); and (2) The area of land under the technology is not reduced in the 3 years of consistent adoption (Bell et al., 2018).

While literature on adoption of SAPs has mainly focussed on single season adoption decisions and the impacts of adoption on livelihood outcomes, research on potential and actual success factors of diffusion over space and time to ensure sustained adoption for sustainable benefits has just emerged (Di Prima et al., 2022; Amadu et al., 2020; and De Brauw et al., 2018). To that extent, the objective of this paper is to model sustained adoption of SAPs under varying agro-ecological conditions. In more detail, we analyse and compare whether the estimates of one-time adoption and sustained adoption are similar in order to inform policy on potential and actual success factors of SAPs diffusion for sustainable benefits. As such, the current paper provides a new perspective to modelling adoption of agricultural technologies including SAPs amidst vast dis-adoption and inconsistent adoption of the practices. The current study hence adds to existing literature in two ways: First, it adds to a new body of literature on sustainability of agriculture interventions by providing a first time shift of modelling SAPs in Malawi by considering consistent and sustained adoption of SAPs to shape future adoption studies and policy frameworks. Thus the first contribution of the paper is methodological in nature as past research has dwelt on whether farmers adopted or practiced the SAP in the past season. The current paper provides evidence of a new perspective in modelling adoption of SAPs for achieving sustainable development of agriculture in Malawi and beyond; Second, it adds to the growing body of literature on adoption of SAPs for scalability of the interventions amidst low and inconsistent adoption rates by providing evidence from a recent and novel large dataset of 2100 farmers in selected climate variability hit areas of Malawi.

2 Materials and Methods

2.1 Study Area

The current study used primary data collected in Mzimba, Kasungu and Mchinji dstricts. Mzimba is located in the northern region of Malawi. The district is the largest in Malawi covering an area of 10,430 Km^2. The district has a total population of 951,119 people and a population density of 92 persons per square kilometer. The district has light-to-medium textured moderately fertile sandy-loam and loamy soils with moderate drainage. On average, maximum temperatures for the district varies from 27°C to 33°C. Minimum temperatures range from 0°C to 10°C. As such, average temperatures for the district range from 15.5°C to 19.8°C. The district's annual precipitation varies from 1.63 mm to 615.64 mm, with an average of 177.87 mm. Kasungu and Mchinji are districts in the central region of Malawi. To start with Kasungu, the district covers an estimated area of 7,878 km which is presided over by a population of about 842,953 people. On average, the district's temperature ranges from 16°C to 33°C. Annual precipitation ranges from 1.95 mm to 399.6 mm, averaging 125.18 mm. Mchinji covers an estimated area of 3,356 square kilometers and harbors a population of close to 602,305 people. Annual temperatures range from 10°C to 30°C, with October being the warmest month averaging 29.46°C and July being the coldest month averaging 11.15°C. The annual precipitation for Mchinji varies from 1.82 mm to 373.15, averaging 116.89 mm (World Bank, 2022).

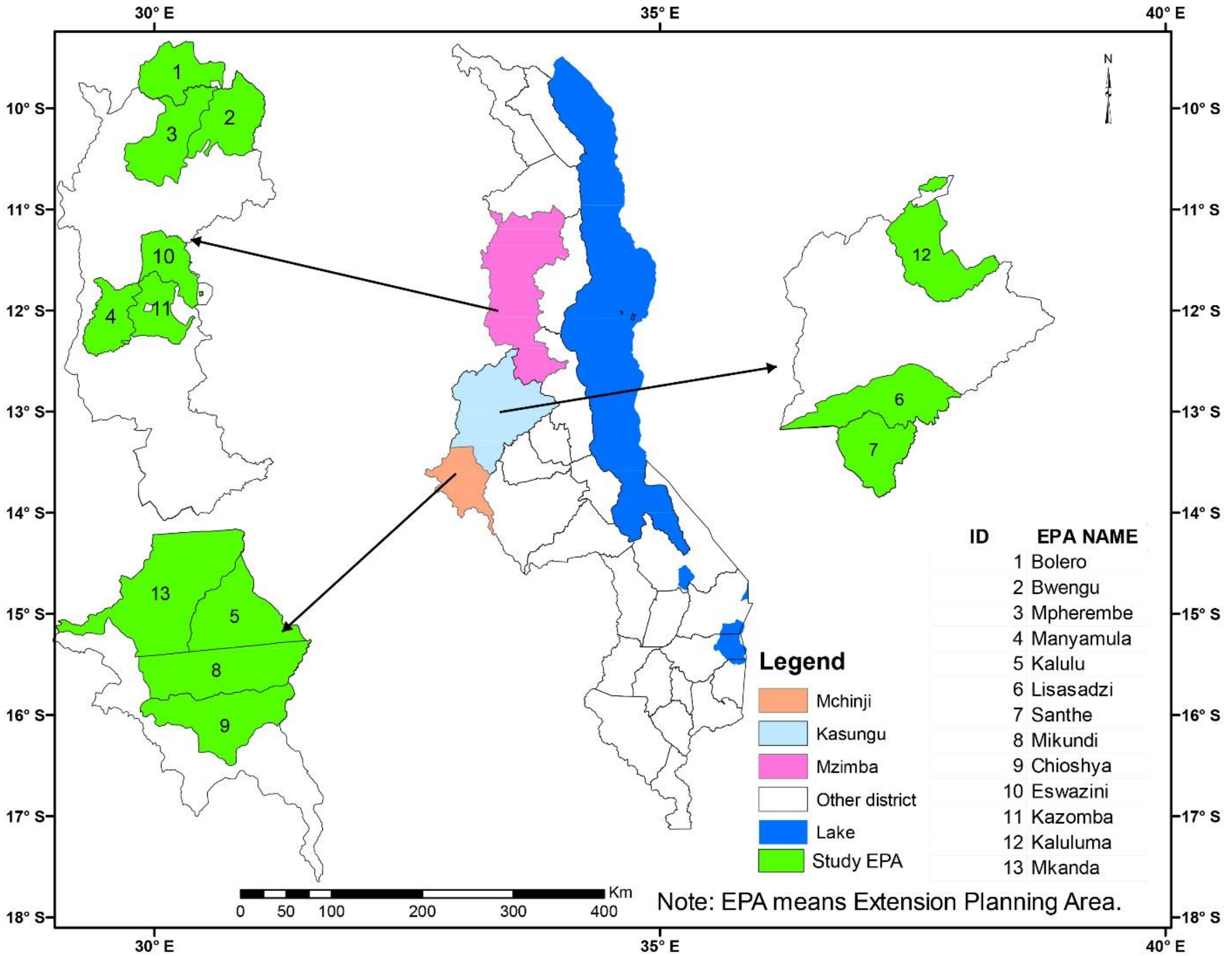

Figure 1: Map of Malawi Showing Study Districts (To be printed in colour)

2.1 Theoretical Framework

2.1.1 Diffusion of Innovation Theory

According to Rodgers (1983), the diffusion of innovation theory is an innovation-based communication that is advocated to a specified group of a social system using some channels over time. Rodger's observation faults most technology advocates who believe that well draped innovations will initiate a natural rapid adoption. Much as it is a possibility that some innovations receive rapid adoption, however in reality, existence of uncertainties and perceived alternatives have resulted in most technologies, including SAPs to be adopted at a slow pace (World Bank, 2020). Rodgers theory acknowledges that diffusion starts with innovation. As such, it is imperious to understand the features of innovation and how they affect the diffusion rate.

Through our review of literature, we note a missed opportunity to fully defining the diffusion process as most social and behavioral studies have ignored the element of time in explaining adoption of agricultural technologies (Sahin, 2006). According to Rodgers (1983), in context, the element of time is acknowledged in the diffusion process but the inclusion of time in most social research has been indirect (*for instance, panel data research*) that it fails to account for reinvention. Furthermore, considering time in the adoption of technologies is crucial as it captures the characteristics of the adopters of the technologies. As such, modelling the SAPs diffusion process complements the relevance of the time element, which we further empirically test using survival duration models.

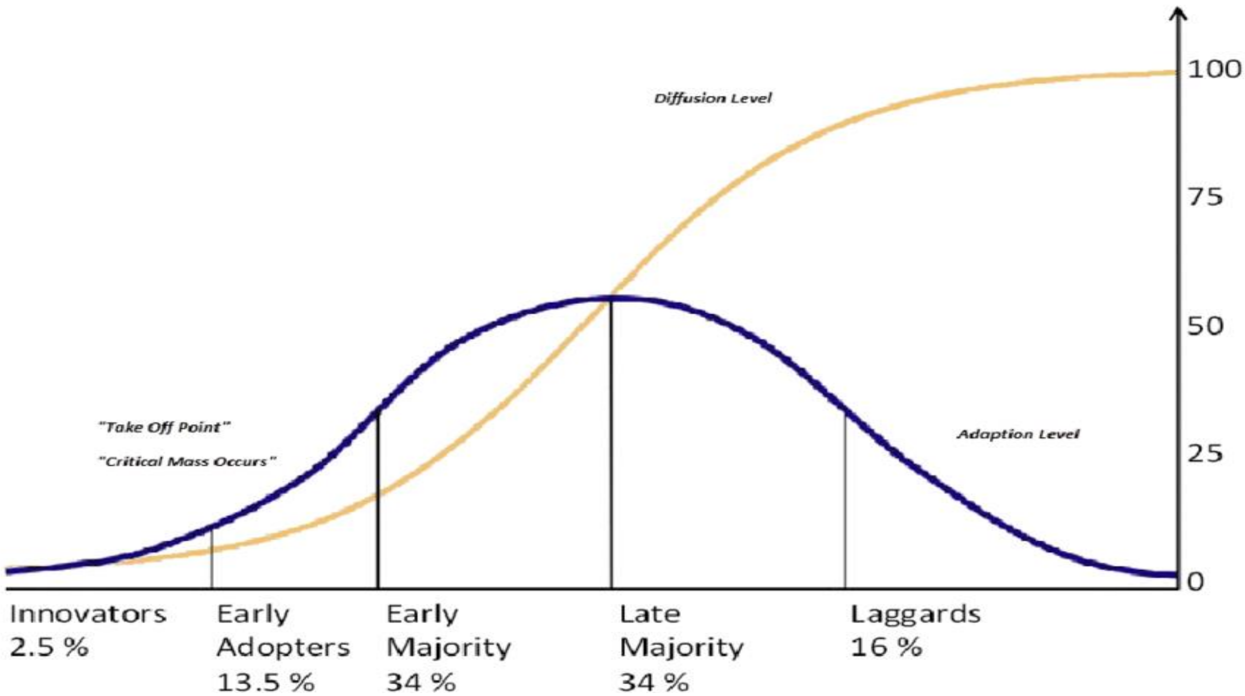

Figure 2: The Curve of Innovation Diffusion

Source: Rodgers (1983)

Having understood Rodgers definition of innovation diffusion, we follow Giovanis and Skiadas (1999) to model uptake of SAPs as follows;

$$\frac{dN(t)}{dt} = g(t)(m - N(t)) \tag{1}$$

Where $N(t)$ is the cumulative number of SAPs adopters at time t; m presents the ultimate ceiling number of potential adopters; and $g(t)$ is the rate of diffusion of the SAPs. However, Bass (1969) proposed that the rate of diffusion $g(t)$ follows a mixed-influence model where diffusion results from both internal and external factors. We present this as follows;

$$\frac{dN(t)}{dt} = (p + \frac{q}{m}N(t))(m - N(t)) \tag{2}$$

Where p is the coefficient of innovation in a mixed-influence model; and q is the coefficient of adoption behavior imitation by neighboring farmers. By extension, if we are to assume that the fraction of the potential adopters who have managed to adopt the SAPs by time t is represented by$F(t)$, then if $F(t) = {}^{N(t)}/_{m}$, then the Bass model can be presented as follows;

$$\frac{dF(t)}{dt} = (p + qF(t))(1 - F(t)) \tag{3}$$

Bass (1969) further assumes that the ceiling potential of the SAPs adopters m is a given constant number, then taking the first order condition of equation (2) with respect to three parameters p, q and m, and further considering a special case where the innovation coefficient p is zero, a simplified version of the Bass model can be presented as follows;

$$\frac{dN(t)}{dt} = \frac{q}{m}N(t)(m - N(t)) \tag{4}$$

According to Bass (1969), equation (4) is a logistic model since the diffusion of innovation is found to follow an S-curve. As such, deriving the diffusion of innovation curve over time $N(t)$ is presented as follows;

$$N(t) = \frac{m}{1+\frac{m-N_0}{N_0}e^{-qt}} \tag{5}$$

Where $N_0 = N(0)$ which is the number of SAPs adopters at time 0. Since this curve follows an S shape, then the number of SAPs adopters is expected to increase at an increasing rate, and then reaches an inflection point over time, and then starts to decrease until it reaches a point of adoption saturation.

However, we deviate from the reasoning of Bass (1969) by assuming that the ceiling number of potential adopters of SAPs cannot be a constant. This is so as climate variability plays a big role in determining adoption of such agricultural practices. Since weather patterns continue to vary over time, then it is expected that the ceiling potential in this particular regard is not constant and follows an exponential function. The exponential model can thus be adapted from Sharif and Ramanathan (1981) who estimated binomial innovation models when faced with a dynamic population of adoption. The exponential ceiling can be defined as follows;

$$m(t) = m_0 e^{gt} \tag{6}$$

As such, we dwell our theoretical foundation on the dynamic diffusion of adoption model which we present as follows;

$$\frac{dN(t)}{dt} = (p + \frac{q}{m(t)}N(t))(m(t) - N(t)) \tag{7}$$

2.1.2 The Utility Maximization Theory

Having defined adoption spells in a technology diffusion process, we further assume that a farmer would sustainably adopt the practice if it maximizes his/her utility. With the utility model, farming households maximize utility from adopting SAPs that yield higher returns (Kassie et al., 2015). If we are to assume an individual farming household i from a sample of N households which has to choose from a given set of SAPs j=1, 2, 3 namely (1) Organic manure; (2) Mulching; and (3) Pit planting. We further assume that each farming household attaches a utility U_{ij} to each sustainable agricultural practice depending on institutional and agro-ecological factors (η_{ij}) and household factors (h_i). Therefore, utility derived by an individual farming household i from adopting practice j can be presented as follows;

$$\mathrm{Uij} = ((\eta\mathrm{ij}, \mathrm{hi}) \qquad \forall j = 1, 2, 3 \tag{8}$$

If we let D_{ij} denote a discrete choice variable for each of the sustainable agricultural practice, and assuming the absence of mutual exclusivity in the choices made by farming households, then D_{ij} takes the value 1 if household i chooses sustainable agricultural practice j and zero otherwise. The corresponding probability can be presented as follows;

$$P_{i1} = \Pr\,(U_{i1} > U_{i2}\,, U_{i1} > U_{i3}\,) \tag{9}$$

This implies that the utility for the given choice of SAP is greater than the utility derived from the other choices. Since the social, institutional and agro-ecological features of the farming household are quite observable, the utility function can then be modelled as follows;

$$U_{ij} = V_{ij} + \varepsilon_{ij} \forall j = 1, 2, 3 \tag{10}$$

Where $V_{ij} = \delta_j X_{ij}$ is the representative farming household utility and the X_{ij} is the vector of observed variables relating to household and institutional characteristics. ε_{ij} is the stochastic error term and it captures the unobservable attributes like farmer personal motivation, and δ_j is the vector of unknown parameters which are to be estimated.

2.2 Empirical Framework

We first acknowledge that a good number of adoption studies have defined adoption as a binary variable of whether or not a farmer practiced the technology in the survey season. However, the current study goes beyond existing literature to redefine adoption as practicing the technology consistently for 3 seasons whilst maintaining the area under the practice, and hence call it sustained adoption.

2.2.1 The Multivariate Probit Model

First, we define one-period adoption and sustained adoption as binary variables for the three practices of organic manure, mulching and pit planting. Multivariate probit models are used to analyze the determinants of one-period and sustained adoption. Second, we run another multivariate probit model to estimate the determinants of dis-adoption of the three practices. Recognizing that we have more than one binary equation with correlated error terms across equations, the multivariate probit model is ideal in that scenario (Capperali & Jenkins, 2003). Assuming three equations with a binary response dependent variable, the adoption of such technologies can be presented as follows;

$$Y_{imt}^{*} = \beta_m' X_{im} + \emptyset C_{it} + \varepsilon_{im} \quad \text{for m=1, 2, 3 and t=1,2,3} \tag{11}$$

$$Y_{imt} = 1 \; if \; Y_{imt}^{*} > 0 \; for \; all \; t \tag{12}$$

$$Y_{imt} = 0 \; if Y_{imt}^{*} \leq 0 \; for \; all \; t \tag{13}$$

Where Y_{imt} indicates the SAPs adopted consistently for the past three years by the smallholder farmer. The farmer in this case consistently adopts if $Y_{imt}^{*} > 0$; X_{im} presents the vector of socioeconomic and institutional factors (see Table 1); β and ∅ presents the vector of parameters that will be estimated. C_{it} presents a vector of agro-ecological factors like rainfall and temperature characteristics that are controlled for farm and area specific variations in climate conditions. It should further be noted that the error term ε_{im} follows a multivariate normal distribution. This implies that the residuals have a zero expected value and a variance-covariance matrix, V which has Ones on the main diagonal and correlations $\rho_{jk} = \rho_{kj}$ in the off diagonal (Wooldridge, 2015).

Following (Greene, 2012), the joint probabilities of adopting SAPs are presented as follows;

$$Y_{imt}|X_{im} \text{ for i=1,2…., n} \tag{14}$$

And these are assumed to form M-variate normal probabilities and are predicted using a likelihood function presented as follows;

$$L_i = \emptyset_m(q_{i1}x'_{i1}\beta_1, \dots \dots . ., q_{im}x'_{im}\beta_m, R^*) \tag{15}$$

Where:

$$q_{im} = 2Y_{imt} - 1 \tag{16}$$

$$R^*_{jm} = q_{ij}q_{im}\rho_{jm} \tag{17}$$

Thus, ρ_{jm} is the correlation coefficient among the pairs of the error terms of the equations, ε_j and ε_m. A correlation coefficient of greater than zero implies that the smallholder farmers indeed do not make independent decisions in adopting the three practices (Rahman & Chima, 2015).

2.2.2 The Cox Proportional Hazard Model

Third, we estimate adoption hazard rates through a Cox Proportional Hazard model. This is so as dis-adoption and inconsistent adoption hinder farmer realization of the benefits of SAPs. We note that survival analysis presents the best fit check as it explains not only the adoption duration but also the hazard rates. Following Lancaster (1992), if we let T to be a nonnegative random variable measuring the adoption spell of SAPs; and if we further assume t to be a realization of T where the observed durations of each smallholder farming household consist a series of data $(t_1 < t_2 <\dots t_n)$. Then the probability density function of t can be given as $f(t)$, and the cumulative density function *F(t)* can be given as follows:

$$F(t) = \int_0^t f(s)ds \tag{18}$$

Where *f(s)* is the adoption duration given as *S(t)* as the survival function;

$$S(t) = P(T > t) = 1 - F(t) \tag{19}$$

Following the adoption survival function, the probability (P) that the spell of adopting SAPs occurs at an infinitesimal time period (Δt), after the non-adoption decision of the SAPs has lasted to time t can be given as follows;

$$P\ (t \leq T < t + \ \Delta t|T > t) \tag{20}$$

What we need most is the probability that a farmer adopts the SAPs at time t such that T=t, given that the farmer did not adopt the SAPs before t, and this can be presented by the hazard function ($h(t)$);

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t | T > t)}{\Delta t} = \frac{f(t)}{S(t)} \tag{21}$$

It should further be noted that a set of independent variables (i.e agro-ecological, socioeconomic and institutional factors) can further affect the distribution of the adoption spell;

$$h(t, x, \theta, \beta) = \lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t | T > t)}{\Delta t} \tag{22}$$

Where x is a vector of socioeconomic, institutional and agro-ecological variables; β is a vector of parameters to be estimated; and θ is a vector of parameters that define the distribution function of the hazard rates. Under the semi-parametric model, the adoption spell of each smallholder farmer is expected to have its own hazard function;

$$h_i(t) = h(t; x_i) = h_0(t) \exp(x_i \beta) = h_0(t) \exp(\beta_1 x_{i1} + .. + \beta_k x_{ik} + \emptyset C_i) \tag{23}$$

Hence;

$$\log h_i(t) = \alpha(t) + \beta_1 x_{i1} + .. + \beta_k x_{ik} \tag{24}$$

Where $\alpha(t) = \log h_0(t)$ and β are the proportional effects of the independent variables on the probability of adoption. C_i presents a vector of agro-ecological factors like rainfall and temperature.

2.2.3 Selection of Best Fit Models

The study estimated pairs (one-time vs sustained adoption) of Multivariate Probit models for each of the SAPs. The idea was to compare the estimates of one-time and sustained adoption. However, it is not an easy task to decide the appropriate model between the two models. Nonetheless, following Wooldridge (2005), an appropriate model is the one with the smallest Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC). These are presented as follows:

$$AIC = 2k - 2\ln(L) \tag{4.25}$$

$$BIC = k ln(n) - 2\ln(L) \tag{4.26}$$

Where AIC is the Akaike Information Criterion; BIC is the Bayesian Information Criterion; k is the number of estimated parameters in the model; n is the number of data points; and L is the maximum value of the likelihood function for the model.

2.2.4 Variables and Expected Signs

We consider various factors from literature and theory likely to affect adoption, and by extension, sustained adoption and adoption duration. Factors considered included socioeconomic (household head age, gender, household size, farming experience, education level, presence of under-five children, land ownership, Total Livestock Units, off-farm work, ownership of a smartphone and ownership of a radio); institutional factors (access to extension services, farmer club membership, savings and loan group membership; received SAPs training, ever listened to SAPs radio programs; ever attended field demonstrations); and agro-ecological factors (3 years average temperature and rainfall, presence of a drought, presence of floods, soil type and perception of soil quality). Table 1 provides a summary of the key independent variables and their expected effect on adoption.

Table 1: Independent Variables and Expected Signs

Independent Variable	Adoption/Sustained Adoption/Adoption Duration expected signs	Reference
Socioeconomic		
Age of HH Head	±	(Ayinde et al., 2017); (Mgomezulu et al., 2018) (Pangapanga-Phiri and Mungatana, 2021)
Farming experience (years)	+	(Pangapanga-Phiri and Mungatana, 2021); (Vaiknoras et al., 2019)
Education of HH head (years)	+	(Pangapanga-Phiri and Mungatana, 2021); (Vaiknoras et al., 2019); (Mgomezulu et al., 2018)
Female HH head (1=yes)	+	(Low and Thiele, 2019);(Mapanje et al., 2021)
Household (HH) size	+	(Low and Thiele, 2019); (Mapanje et al., 2021); (Ayinde et al., 2017)
Land ownership (acre)	±	(Mapanje et al., 2021); (Bell et al., 2018)
Total Livestock Units (TLU)	+	(Musa et al., 2015)
Smartphone (1=yes)	+	(Ojha and Khanal, 2021)

Radio (1=yes)	+	(Ojha and Khanal, 2021); (Ayinde et al., 2017)
Institutional Factors		
Access to extension (yes/no)	+	(Mapanje et al., 2021); (Pangapanga-Phiri and Mungatana, 2021)
Farmer clubs / association membership (yes/no)	+	(Vaiknoras et al., 2019)
Saving/credit group membership (yes/no)	+	(Pangapanga-Phiri and Mungatana, 2021)
Received SAPs training (yes/no)	+	(Low and Thiele, 2019)
Ever listened to SAPs radio program (yes/no)	+	(Low and Thiele, 2019); (Vaiknoras et al., 2019)
Ever attended field demos (yes/no)	+	(Low and Thiele, 2019)
Agroecological Factors		
Rainfall (mm)	−	(Serdeczny et al., 2016)
Temperature (degrees Celsius)	±	(Serdeczny et al., 2016)
Soil type (1=sandy)	+	(Bachewe et al., 2019)
Soil quality (1=poor)	+	(Bachewe et al., 2019)

2.2.4 Data

The study collected a rich and robust dataset of 2100 randomly selected households from 349 randomly sampled Enumeration Areas (EAs) in the 3 districts of Mzimba, Kasungu and Mchinji. We further supplement quantitative data with qualitative (Focus Group Discussion and Key Informant Interviews i.e. extension workers) data collected from the EAs. The EAs were randomly sampled in order to prevent any sort of sampling bias. Again, we included rainfall and temperature data, and further controlled for soil type and perception of soil quality which were crucial determinants of SAPs (Bachewe et al., 2019), and these form part of the agro-ecological factors. Average monthly rainfall and temperature data for the past 3 years covering the sampled districts and EAs were hence requested from CEDA (Center for Environmental Analysis). These data were matched with the three-years data for the same years on adoption of SAPs. Following Dessy et al. (2020), we merged farmer characteristics with the computed average rainfall and temperature data from CEDA using the collected GPS coordinates. Following NSO (2020), proportional sampling to size of the districts was adopted and hence we calculated sample weights which was the inverse of the probability of selecting farmers in the districts. Table 2 provides the details of the final samples.

Table 2: Proportion Sampling to Size in the 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

3 Results and Discussions

3.1 Descriptive Statistics

Table 3 presents the characteristics of the sampled farming households. On average, a household comprised of 4 people; household heads spent between 5.7 to 7.4 years of effective years in school; the average age of household heads was around 44 years; households owned around 3.3 acres of land; average Total Livestock Units ranged between 0.59 to 0.68; the three year monthly average temperature was around 21 degrees and precipitation was around 81mm a year; most households didn't have children under five years of age with an average number of children around 0.4; adoption duration of SAPs ranged from 3.4 to 3.9 years. Other pertinent factors included perception of soil quality where more than 60% perceived the soil to be fair and good, with a substantial proportion reporting to have loam and sandy loam soils. More than 80% of the household heads were males; more than 7 in every 10 households reported to have experienced a dry spell in the past 3 years; almost half of the farmers belonged to a farmer club with more than 8 in every 10 farmers attending SAPs field demonstrations, listening to SAPs radio programs and receiving SAPs trainings. Nonetheless, dis-adoption rates existed amongst organic manure adopters (22.9%), mulching adopters (27.2%) and pit planting adopters (20.2%).

Table 3: Summary of Socioeconomic, Institutional and Agro-ecological Characteristics

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

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)
3 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)
3 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)
Adoption duration	years		3.5 (3.51)		3.4 (1.49)		3.9 (1.1)
District (%)	Mzimba	46.26	44.06	49.42*	46.11	48.99*	45.49
	Kasungu	36.65	37.75	35.66	36.98	42.93	45.08
	Mchinji	17.08	18.18	14.93	16.92	8.08	9.43
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	0.818	0.817	0.815	0.823*	0.807
Radio ownership	Yes (1/0)	0.246	0.233	0.202	0.191	0.196	0.192
Smart Phone ownership	Yes (1/0)	0.034	0.037	0.023	0.020	0.005	0.016
Savings group membership	Yes (1/0)	0.271	0.260	0.281	0.260	0.196	0.176
Farmer club membership	Yes (1/0)	0.514	0.497	0.565	0.538	0.479	0.438
Attended SAPs field demonstrations	Yes (1/0)	0.807	0.793	0.882	0.877	0.904	0.893

Listened SAPs Radio program	Yes (1/0)	0.832	0.825	0.930	0.919	0.954	0.938
Received SAPs training	Yes (1/0)	0.798	0.786	0.850	0.842	0.898	0.885
Extension visit in last 12 months	Yes (1/0)	0.704	0.687	0.759	0.752	0.813	0.790
Dis-adoption	Yes (1/0)	0.229		0.272		0.202	

Standard deviation in parentheses
* *p<0.1*

3.2 Determinants of One-time and Sustained Adoption

Findings from two distinct Multivariate Probit models of one-time and sustained adoption were estimated for mulching, organic manure and pit-planting (Table 4). Both models were significant at 1% indicating the existence of factors influencing adoption choices. The null hypothesis that uptake of the three technologies is unrelated was rejected for each model at 1% significance level, necessitating the use of Multivariate Probit model. Following Wooldridge (2015), the study further computed the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to ascertain the best model between one-time and sustained estimates. Table 4.2 shows that sustained adoption models had the smallest AIC and BIC, implying that they were best fit models as compared to all one-time adoption models which had higher AIC and BIC.

Organic Manure

As earlier alluded to, we estimate models of sustained adoption and one-time adoption decisions for the three SAPs. To start with, a person increase in household size increased the probability of sustainably adopting organic manure by 1.5% and did not affect the one-time adoption model decision. Household size is a proxy for family labor, as such, bigger household sizes allow for adoption of labor intensive technologies (Oyawole et al., 2019). With regards to geography, farmers in Kasungu had a 9.1% percent probability (more than that of reference group of Mzimba) of one-time adoption but not sustained adoption. It was noted through FGDs that most farmers in Kasungu applied organic manure as they complained about the soil structure and its ability to retain moisture. Similarly, age of household head increased the probability of one-time adoption decision but failed to affect sustained adoption. Likewise, a unit increase in land size increased the probability of one-time adoption decision but failed to influence sustainable adoption. Through the Focus Group Discussions (FGDs), it was realized that it takes much labor, time, and raw materials to make manure for an acre. As such, farmers fail to produce manure for a big piece of land as the process is hectic. Again, ownership of a smart phone increased the probability of one-time adoption decision by 11.2% whilst an increase in total livestock units sustainably increased one-time adoption by 2.6%.

Mulching

Similarly, some factors affected one of the adoption models whilst some affected both one-time and sustained adoption decisions. For instance, farmers from Mchinji district had a significant negative effect on one-time adoption and insignificant effect on sustained adoption. Thus farmers from mchinji had a 7.9% less probability of one-time adoption as compared to the reference group of Mzimba. FGDs with farmers from the district revealed that mulching was associated with bringing pests like termites in the maize fields hence the negative adoption. Age of the household head had a positive and significant effect on sustained adoption only. Age is a proxy of experience and hence older farmers with more experience understand the technology with time, leading to sustained adoption. Ownership of a radio also influenced sustained adoption alone. Lastly, an increase in average temperature significantly reduced the probability of one-time adoption but significantly increased the probability of sustained adoption. KIIs with extension officers revealed that mulching help retain moisture in the soil during high temperatures. Namaghi et al. (2018) in their agronomic study noted that yields were significantly affected by changes in soil moisture and temperature as a result of different levels of mulching, such that high levels of mulching were associated with reduced soil temperature and high moisture content. To that extent, increased 3 year average temperatures increased the probability of sustained adoption of mulching as opposed to one-time adoption decision.

Nonetheless, a number of other factors affected both one-time and sustained adoption decisions. These include total livestock units, soil type, perception of soil quality, savings group membership, farmer's club membership, attending field demonstrations and receiving SAPs training.

Pit Planting

Similarly, some factors affected only one of the adoption models and some affected both of the adoption models. For instance, age of the household head reduced the probability of one-time adoption but had no effect on sustained adoption. FGDs findings further revealed that the youth participate more in labour intensive technologies like pit planting as it is tedious to dig planting holes for more than an acre. Again, farmers with loamy soils had a 23.88% less probability of one-time adoption as compared to the reference group of sandy soils. This is so loamy soils have a good compact structure as opposed to the porous soil structure found in sandy soils. Again, attending field demonstrations increased the probability of sustained adoption by 3.4% and had no effect on one-time adoption. KIIs with extension officers revealed that the demonstrations help to provide step-by-step practical presentations of how to implement the technologies hence makes it easier for farmers to implement the practices over time. Again, an increase in total livestock units increased the probability of sustained adoption. Since livestock are mostly liquidated to obtain cash for the use of labour in labour intensive technologies, those with more valuable livestock assets are better able to sustain the practice. Lastly, an increase in average temperature reduced the one-time adoption of pit planting and not sustained adoption. Scientists have associated pit planting with erosion control, moisture infiltration and preventing soil degradation (World Bank, 2018); (Bedeke et al., 2019); and (Ekman, 2021), hence the no significant effect on sustained adoption. However, the negative effect on one-time adoption can be associated to farmer's perceptions that pit planting helps reduce evaporation of water in hot seasons as mostly expressed in FGDs. Nonetheless, overtime with experience, the effect of temperature on sustained adoption is negated.

Table 4: Estimating Factors Influencing One-time and Sustained Adoption of SAPs in Malawi

Explanatory Variables	**Organic Manure**	**Organic Manure**	**Mulching**	**Mulching**	**Pit Planting**	**Pit Planting**
	One-time adoption	*Sustained Adoption*	*One-time adoption*	*Sustained Adoption*	*One-time adoption*	*Sustained Adoption*
HH_Size	0.0104	0.0146**	-0.0034	-0.0034	0.0689**	0.0140***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.030)	(0.004)
HH_educa	0.0081***	0.0109***	-0.0047*	-0.0058**	-0.0554***	-0.0078***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.014)	(0.002)
Kasungu	0.0912**	0.0596	0.0089	0.0378	0.3007	0.0458
	(0.046)	(0.048)	(0.042)	(0.043)	(0.195)	(0.033)
Mchinji	-0.0292	-0.0327	-0.0788**	-0.0326	-0.3732*	-0.0490**
	(0.040)	(0.043)	(0.037)	(0.038)	(0.208)	(0.024)
HH_sex	0.0130	0.0037	0.0271	0.0248	0.1024	0.0061
	(0.025)	(0.026)	(0.023)	(0.024)	(0.121)	(0.018)
HH_Age	0.0024***	0.0007	0.0011	0.0014**	-0.0063*	-0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)
Offfarm	-0.0659	0.0653	-0.0033	0.0218	0.000	-0.0945
	(0.062)	(0.060)	(0.055)	(0.054)	(0.223)	(0.065)
Children	-0.0046	0.0085	0.0217	0.0240	-0.1046	-0.0181
	(0.018)	(0.019)	(0.017)	(0.017)	(0.088)	(0.013)
Land (acres)	0.0059*	0.0037	0.0029	0.0022	0.0184	0.0012
	(0.003)	(0.004)	(0.003)	(0.003)	(0.013)	(0.002)
Radio	0.0377	0.0142	-0.0349	-0.0437*	-0.0175	-0.0003
	(0.025)	(0.026)	(0.022)	(0.023)	(0.114)	(0.017)

Smart_Phone	0.1117**	0.0600	0.0568	0.0011	-0.3991	0.0316
	(0.057)	(0.059)	(0.055)	(0.057)	(0.470)	(0.048)
TLU	0.0056	0.0264**	0.0142*	0.0160**	0.0488	0.0084*
	(0.008)	(0.011)	(0.007)	(0.008)	(0.033)	(0.005)
Soil type: Loam	0.0153	-0.0561*	0.0709**	0.1024***	-0.2388*	-0.0162
	(0.032)	(0.033)	(0.028)	(0.029)	(0.139)	(0.022)
Soil type: Sandyloam	0.0697**	0.0715**	-0.0147	0.0070	-0.2181	-0.0130
	(0.032)	(0.033)	(0.027)	(0.028)	(0.140)	(0.022)
Soil type: Clay	0.0403	0.0503	0.1045**	0.1225***	-0.3457	-0.0249
	(0.046)	(0.048)	(0.041)	(0.041)	(0.230)	(0.032)
Soil quality: Fair	0.0737***	0.1275***	-0.1968***	-0.2273***	-0.7152***	-0.1483***
	(0.027)	(0.028)	(0.026)	(0.027)	(0.118)	(0.025)
Soil quality: Good	0.0842**	0.0749**	-0.1661***	-0.1960***	-0.5800***	-0.1328***
	(0.034)	(0.035)	(0.032)	(0.033)	(0.149)	(0.029)
Floods in past 3 years	0.0652*	0.0252	-0.1113***	-0.1260***	-0.2698	-0.0452
	(0.039)	(0.041)	(0.039)	(0.040)	(0.217)	(0.031)
Dry spell in past 3 yrs	-0.0154	-0.0368	0.1429***	0.1373***	0.0296	-0.0058
	(0.022)	(0.023)	(0.022)	(0.022)	(0.112)	(0.016)
Savings groups	0.2010***	0.2705***	0.0712***	0.0573**	0.0336	0.0094
	(0.029)	(0.030)	(0.025)	(0.026)	(0.134)	(0.020)
Farmer club membership	0.0330	-0.0082	0.0709***	0.0644***	0.1665	0.0084
	(0.024)	(0.025)	(0.021)	(0.022)	(0.111)	(0.017)
Field demonstrations	0.0273	0.0272	0.0989***	0.1139***	0.1831	0.0342*
	(0.026)	(0.026)	(0.025)	(0.025)	(0.144)	(0.020)
Listened SAPs	0.0220	0.0179	0.1192***	0.0991***	0.5233***	0.0616***

Radio program						
	(0.028)	(0.028)	(0.028)	(0.028)	(0.175)	(0.023)
SAPs_training	0.2130***	0.3158***	0.2454***	0.2617***	0.7499***	0.1226***
	(0.022)	(0.021)	(0.020)	(0.020)	(0.132)	(0.019)
extension_visited	0.0238	-0.0243	0.0181	0.0124	0.3145**	0.0362**
	(0.024)	(0.024)	(0.022)	(0.023)	(0.126)	(0.018)
year_3_avg_temp (celcius)	-0.0208	-0.0053	-0.0360**	-0.0352*	-0.1923**	-0.0200
	(0.021)	(0.022)	(0.018)	(0.019)	(0.084)	(0.013)
year_3_avg_rain (mm)	-0.0077***	-0.0038*	-0.0017	-0.0020	-0.0111	-0.0006
	(0.002)	0.0003)	(0.002)	(0.002)	(0.009)	0.0027)
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
AIC	1188.74	1106.34	1191.22	1083.12	1176.52	1081.01
BIC	1201.22	1038.18	1211.01	1088.73	1188.78	1028.18

LR chi2 (81) = 1364.44; rho_12 = rho_13 = rho_23 = 0; P-value=0.000

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

3.3 Robustness Checks

3.3.1 Determinants of Dis-adoption of SAPs

Having noticed that dis-adoption rates of such SAPs revolved around 20% to 27%, the study further sought to pin point the determinants of dis-adoption of such practices. The results are presented in Table 5 using marginal effects. The overall model was significant at 1%. The null hypothesis that the dis-adoption decisions are unrelated was reject at 1% implying the need for estimating a multivariate probit model. Number of effective years spent in school significantly reduced dis-adoption of mulching and pit planting; older household heads had a higher probability of dis-adopting mulching; an increase in number of children (under-five) in the household reduced the probability of dis-adopting organic manure by 2.6%; ownership of a radio reduced the probability of dis-adoption of mulching by 3.8%; ownership of a smart phone reduced the probability of dis-adoption of pit planting by 7.6%; farmers with loamy soils had a 47% and 36% probability of dis-adopting mulching and pit planting respectively whilst those with sandy loam soils had a 36.1% of dis-adopting pit planting; those who perceived their soils quality to be fair had a 95.7% less probability of dis-adopting as compared to those that perceived their soils to be poor; membership of a savings group reduced the probability of organic manure dis-adoption by

4.7% and dis-adoption of mulching by 3.97%. Furthermore, SAPs knowledge and training factors were found to be significant factors of reducing dis-adoption. For instance, listening to SAPs radio programs was found to reduce the likelihood of dis-adoption of organic manure and mulching by 8.3% and 4% respectively. Receiving SAPs training reduced the likelihood dis-adoption of organic manure, mulching and pit planting by 2.48%, 9.58% and 5.37% respectively. This shows the need for intensifying SAPs related information dissemination in order to lower dis-adoption rates and ensure sustained adoption.

Table 5: Estimating Factors Influencing Dis-adoption of SAPs among Smallholder Farmers in Malawi

Explanatory variables	Organic Manure	Mulching	Pit Planting
	dy/dx	dy/dx	dy/dx
HH_Size	0.0039	0.0029	0.0042
	(0.003)	(0.004)	(0.003)
HH_educa	0.0009	-0.0064***	-0.0032***
	(0.002)	(0.002)	(0.001)
Kasungu	-0.0019	0.3422	0.4731
	(0.024)	(0.228)	(0.288)
Mchinji	0.0354	0.3422	-0.3963
	(0.025)	(0.228)	(0.353)
HH_sex	0.0179	0.0071	-0.0064
	(0.014)	(0.014)	(0.010)
HH_Age	0.0003	0.0008*	0.0001
	(0.000)	(0.000)	(0.000)
Land (acres)	-0.0003	-0.0005	0.0011
	(0.002)	(0.002)	(0.001)
Radio	-0.0184	-0.0382**	-0.0075
	(0.013)	(0.016)	(0.012)
Smart_Phone	0.0364		-0.0764***
	(0.024)		(0.028)
TLU	0.0054	0.0079*	0.0014
	(0.004)	(0.004)	(0.004)
Soil type: Loam	-0.0124	0.473***	0.360***
	(0.018)	(0.159)	(0.193)
Soil type: Sandyloam	-0.0247	0.2095	0.3608***
	(0.017)	(0.164)	(0.193)
Soil type: Clay	0.0030	0.2722	0.0878
	(0.025)	(0.238)	(0.201)
Soil quality: Fair	-0.0079	-0.939	-0.957***
	(0.015)	(0.118)	(0.148)
Soil quality: Good	-0.0267	-1.237***	-1.366***
	(0.016)	(0.184)	(0.261)
Savings groups	0.0470***	-0.0397**	-0.0217
	(0.015)	(0.019)	(0.017)

Farmer club membership	-0.0125	-0.0123	-0.0244**
	(0.014)	(0.014)	(0.011)
Field demonstrations	-0.0393***	0.0245	-0.0241*
	(0.013)	(0.016)	(0.013)
Listened SAPs Radio program	0.0828***	0.0404**	0.0167
	(0.018)	(0.018)	(0.014)
SAPs_training	-0.0248**	-0.0958***	-0.0537***
	(0.012)	(0.015)	(0.012)
extension_visited	-0.0211*	-0.0129	0.0011
	(0.012)	(0.013)	(0.010)
year_3_avg_temp (celcius)	0.0018	-0.0290***	-0.0112
	(0.011)	(0.010)	(0.007)
year_3_avg_rain (mm)	0.0016	-0.0003	0.0009
Prob > chi2	0.000	0.000	0.000

LR chi2 (87) = 1364.44; rho_12 = rho_13 = rho_23 = 0; P-value=0.000

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

3.3.2 Cox Proportional Hazard Model for Adoption of SAPs

In order to cement the need for emphasizing on sustained adoption decisions, we estimate survival functions and their respective hazard rates to understand the relative risk of dis-adoption. Figures 3 through 5 provides the Kaplan Meier survival estimate and the Nelson Aalen cumulative hazard estimate for organic manure, mulching and pit palnting in that order. The Kaplan Meier survival estimates results show that survival durations of organic manure, mulching and pit planting were 46, 15 and 7 years respectively. For organic manure adoption (Figure 3), the probability of survival dropped from 100% in the first year to around 30% in the next 5 years and to 0% at 20 years to 46 years. On the other hand, the risk of dis-adoption (hazard rate) increased at a rapid rate from 0.1 in the first year to 2 in the next 10 years, then to 4 in 20 years and later around 6 in the 46 years.

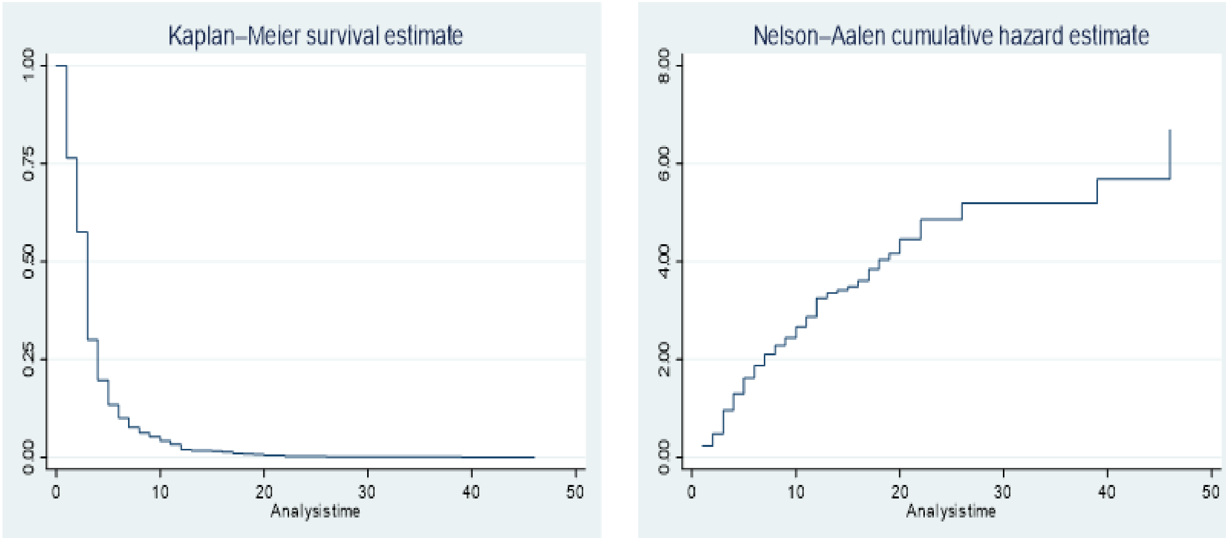

Figure 3: Survival Estimate (left) and Hazard Estimate (right) of Adoption of Organic Manure

For mulching (Figure 4), the probability of survival dropped from 100% in the first year to 25% in 3 years, and later to 0% in 7 years. The hazard estimate shows that the risk of dis-adoption moved from 1 in the first year and doubled to 2 in the first 5 years, later to 5 in 10 years where it remained constant for the next 5 years.

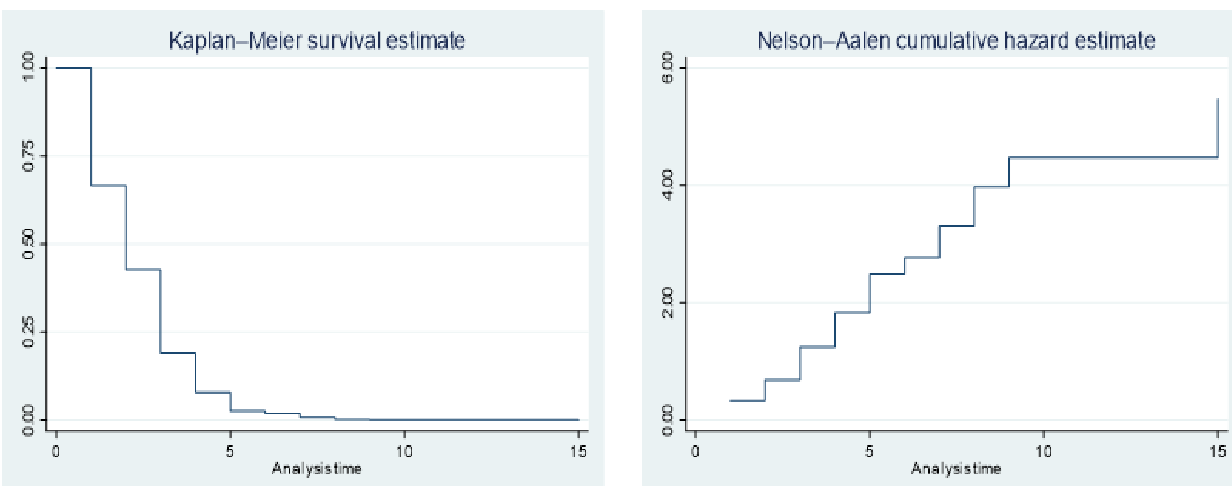

Figure 4: Survival Estimate (left) and Hazard Estimate (right) of Adoption of Mulching

For pit planting (Figure 5), the probability of survival fell dramatically from 100% in the first year to 25% in the second year, and then to 0% in 5 years. The hazard rate increased from 0.5 in the second year to 3.5 in the first 6 years.

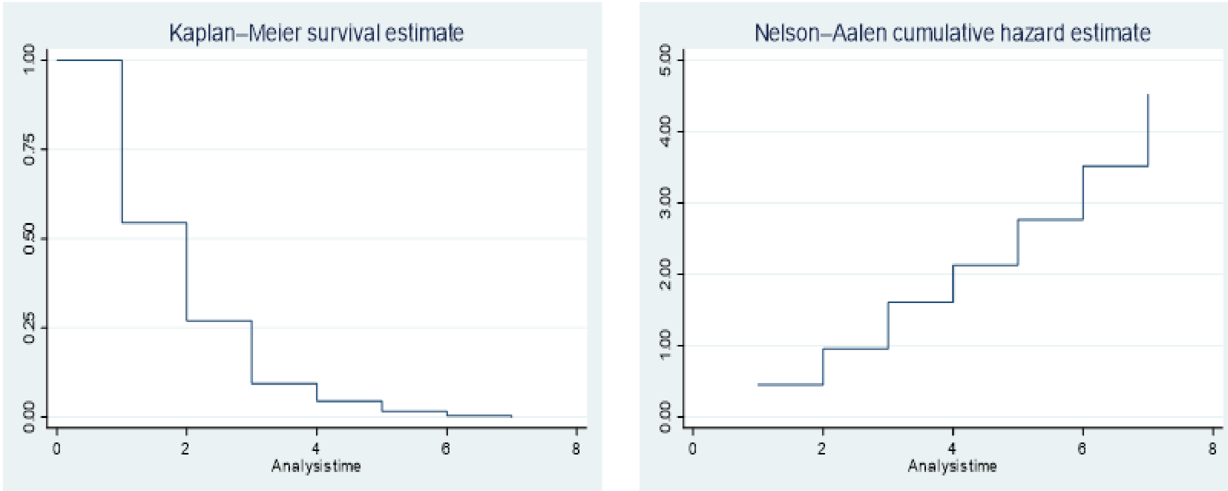

Figure 5: Survival Estimate (left) and Hazard Estimate (right) of Adoption of Pit Planting

The parametric findings show that the probability of sustaining adoption of the three practices significantly drops with time and its worse with pit planting and mulching in that order. Again, the risk of dis-adoption rapidly increases over time.

Table 6 presents the time to failure analysis results of a semi-parametric Cox Proportional Hazard model to understand the relative risk of dis-adoption over time. The overall model was significant at 1%. Furthermore, we fail to reject the Schoenfeld test (Table 7 in appendix) for proportionality assumption at 10%. The hazard ratios happen out of one (Kallas et al., 2018), hence the estimates in Table 6 are the hazard ratios minus one in order to get the relative risk. The findings reveal that more educated had 2.5% lower risk of dis-adopting mulching. This shows that education has a significant effect on sustained adoption of mulching. Male farmers had a 16.98% more risk of dis-adopting organic manure as compared to female farmers. FGDs revealed that most of the farmers that participate in the adoption of organic manure are female farmers who are more vulnerable and lack enough income to purchase organic fertilizers. Membership of a savings group reduced the risk of dis-adopting organic manure and mulching by 20.13% and 48.32% respectively. This shows that access to finances improved the sustainability of the practices. Lastly, listening to SAPs radio programs and receiving SAPs training reduced the relative risk of dis-adopting mulching by 33.91% and 29.78% respectively. KIIs with extension officers revealed that farmers capacitated with SAPs knowledge and information know how to implement the practices for better results and consistently implement the technologies on their farms.

Table 6: Estimating Hazard Ratios (Relative Risk) for the Dis-adoption of SAPs among Smallholder Farmers in Malawi

Explanatory Variables	Organic Manure	Mulching	Pit Planting
	Hazard Ratio	Hazard Ratio	Hazard Ratio
HH_Size	-0.0338	-0.0245	-0.0415
	(0.023)	(0.030)	(0.050)
HH_educa	-0.0169	-0.0251**	0.0303
	(0.011)	(0.012)	(0.021)

Kasungu	-0.3937**	-0.0988	0.2106
	(0.165)	(0.185)	(0.314)
Mchinji	-0.5167***	0.3520*	0.1219
	(0.154)	(0.184)	(0.382)
HH_sex	0.1698*	0.0239	0.0603
	(0.093)	(0.109)	(0.188)
HH_Age	-0.0126***	-0.0001	0.0021
	(0.003)	(0.004)	(0.006)
Land (acres)	-0.0000	-0.0257*	-0.0052
	(0.013)	(0.014)	(0.016)
Radio	-0.1148	-0.1699	-0.0605
	(0.085)	(0.109)	(0.194)
Smart_Phone	-0.2308	-0.5307*	-0.1270
	(0.201)	(0.300)	(0.679)
TLU	-0.0387	-0.0033	-0.0139
	(0.029)	(0.031)	(0.052)
Soil type: Loam	-0.3259***	-0.1000	0.2866
	(0.123)	(0.135)	(0.201)
Soil type: Sandyloam	-0.1854	-0.0818	0.2764
	(0.119)	(0.140)	(0.213)
Soil type: Clay	-0.5043***	-0.0491	0.8692*
	(0.170)	(0.194)	(0.463)
Soil quality: Fair	0.1486	-0.4293***	-0.5221***
	(0.114)	(0.110)	(0.192)
Soil quality: Good	0.0570	-0.6410***	-0.8524***
	(0.138)	(0.143)	(0.251)
savings	-0.2013*	-0.4832***	-0.2994
	(0.104)	(0.120)	(0.263)
Club	-0.1031	-0.1370	-0.2655
	(0.091)	(0.108)	(0.187)
SAPs_Demo	0.1489	0.0764	0.1383
	(0.096)	(0.141)	(0.269)
SAPs_Radio	-0.1623	-0.3391**	-0.1594
	(0.101)	(0.165)	(0.302)
SAPs_training	0.0962	-0.2978**	-0.0473
	(0.094)	(0.125)	(0.260)
extension_visit	-0.0534	-0.1935	-0.1197
	(0.088)	(0.119)	(0.206)
year_3_avg_temp	0.0894	-0.0105	-0.1699
	(0.073)	(0.082)	(0.130)
year_3_avg_rain	0.0058	0.0036	0.0049
	(0.008)	(0.008)	(0.014)
Wald chi	107.7886	126.9198	40.5036
Prob > chi2	0.0000	0.0000	0.0049

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

4. Conclusions and Recommendations

The current study sought to understand farmer's decision dynamics in the adoption of SAPs, with an emphasis of ensuring sustained adoption of the practices. To that extent, the study assessed farmer adoption decisions dynamics amidst vast findings and recommendations from similar studies assessing adoption of SAPs. Since a majority of past studies on adoption of SAPs have treated adoption as a one-time adoption decision, the current study proposed a paradigm shift in modelling adoption decisions in an effort to achieve sustainable development of agriculture in Malawi.

The study further assessed the determinants of dis-adoption to draw policy priority areas. Of key interest were the SAPs knowledge and training factors which significantly reduced the likelihood and risk of dis-adoption. These include listening to SAPs radio programs, attending field demonstrations, getting extension visits, receiving SAPs trainings and being members of savings groups and farmer clubs. These factors have considerable implications to policy makers.

With regards to future research, the study further recommends a modelling shift towards sustained adoption for effective policy design on adoption of SAPs amidst vast dis-adoption and inconsistent adoption. This will ensure that research on adoption of SAPs contributes to achieving sustainable development of agriculture in Malawi. Lastly, the study recommends further research to complement the quantitative modelling approach adopted by the current study. Thus further studies should adopt a qualitative case study research design that explores different phenomena in order to fully understand sustained adoption of SAPs.

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Appendix

Table 7: The Cox Proportional Hazard Model Test for Proportionality

Schoenfeld	**Null Hypothesis**	**Chi-Square Value**	**P-Value**
Global test	Proportionality	6.27	0.219