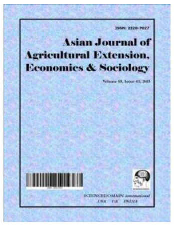

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Determinants of Climate Smart Agriculture Technology Adoption in the Drought Prone Districts of Malawi using a Multivariate Probit Analysis

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Authors' contributions

The paper is an extract based on the first author's PhD work at Lilongwe University of Agriculture and Natural Resources and the other authors are the supervisors who guided this work. All authors read and approved the final manuscript.

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ABSTRACT

Climate variability is one of the limiting factors to increasing per capita food production for most smallholder farmers in Africa. The adoption and diffusion of climate smart agriculture technologies, as a way to tackle this barrier, has become an important issue in the development policy agenda for sub-Saharan Africa. This paper examines the adoption decisions for climate smart agriculture technologies using cross sectional household data, collected in 2014 from 619 farm households, in 2 districts of southern Malawi. In contrast to other studies that analyse technology adoption decisions separately, we analyse all four adoption decisions simultaneously using the multivariate probit method. This not only improves the precision of the estimation results and provides consistent standard errors of the estimates, but also enables us to analyse the interrelations between the four adoption decisions. This study shows how the estimation results, and particularly the estimated correlation coefficients, can be utilized to gain a deep insight into the interrelations between the different adoption decisions. The study reveals that gender, age, location, farmer type, level of education, livelihood status/ off-farm participation, land size and source/ownership,

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household income, household expenditure, anticipated weather pattern, climate variability knowledge/signs, access to credit, all influence the adoption decision of Climate Smart Technologies either positively or negatively.

Keywords: Climate variability; climate smart agriculture technologies; adoption; multivariate probit, smallholder farmers.

1. INTRODUCTION

When it comes to the adoption of a new technology, farmers are faced with choices and trade-offs. Differences in adoption decisions are often due to the fact that farmers have different cultures, different resource endowments, different objectives, different preferences, and different socio-economic backgrounds [1]. It follows that some farmers adopt the new technology while others do not. Rogers defined the rate of adoption as "the relative speed with which an innovation is adopted by members of a social system" [2]. In such a context, farmers' decisions regarding the adoption of innovation can be explained using the theory of the maximization of expected utility. Following this theory, a farmer will adopt a given new technology if the expected utility obtained from the technology exceeds that of the old one [3]. Farmers do adopt a mix of technologies to deal with a multitude of agricultural production constraints. This implies that the adoption decision is inherently multivariate, and attempting univariate modeling would exclude useful economic information about interdependent and simultaneous adoption decisions [4]. When farmers face multiple innovations, they consider the way these different technologies interact and take these interdependencies into account in their adoption decisions. Ignoring these interdependencies can lead to inconsistent policy recommendations [5]. Adoption of CSA technologies has become a major consideration to most smallholder farmers in Malawi. Adoption in this respect is defined as a process of implementing CSA techniques after being aware of the presence of the technologies in one's environment which is heavily affected by climate variability. The study applied a multivariate model to investigate determinants of CSA technology.

A diverse set of potential household-level determinants of adaptive capacity such as household size, age, gender and education level of the household head are considered. For example family size in terms of adult equivalent units is a potential indicator of labour supply for production and if considered in investments, and maintenance of soil and water conservation which are particularly labour demanding and may be too expensive to undertake in households with limited access to labour. Considering the inconsistent estimates culminating from single equation statistical model, where information on a farmer's adoption of one CSA's does not alter the likelihood of the farmer adopting another CSA's. The MVP approach simultaneously models the influence of the set of explanatory variables on each of the different practices, while allowing for the potential correlation between unobserved disturbances, as well as the relationship between the adoptions of different practices [6]. One source of correlation may be complementarities (positive correlation) and substitutability's (negative correlation) between different practices. Failure to capture unobserved factors and interrelationships among adoption decisions regarding different practices will lead to bias and inefficient estimates [7]. The econometric specification in this study examines the determinants of multiple adoption decisions of CSA's, using a multivariate probit model (MVP). In contrast to other models that analyse technology adoption decisions separately, all five adoption decisions were simultaneously analysed using the multivariate probit model. This does not only improve the precision of the estimation results, it also provides consistent standard errors of the estimates and enables an analysis of interrelations between the different adoption decisions.

1.1 Conceptual Framework

The observed outcome of a CSA's adoption can be modelled following random utility formulation as per the method used by Teklewold in their study "adoption of multiple sustainable agricultural practices in rural Ethiopia [8]," with some modification as presented here. If we consider the i^{th} farm household $(i = 1, \ldots, \ldots N)$ which is facing a decision on whether or not to adopt the available CSA's on its plot $p(p = 1, \ldots, \ldots P)$. We can let $U_0 = Z_a$ represent the benefits to the farmer from traditional management practices (zero adaptation), and let U_k represent the benefit of adopting the k^{th} technology: $(k = Pd, Sw, Sfi, Iwh)$ denoting choice portfolio diversification (Pd), soil & water conservation (Sw), soil fertility improvement (Sfi), and irrigation and water harvesting (Iwh). The farmer decides to adopt the k^{th} technology if $Y_{ipk}^{*} = U_k^{*} - U_0 > 0$. The net benefit Y_{ipk}^{*} that the farmer derives from the k^{th} technology is a latent variable determined by observed household, farmer and location characteristics X_{ip} and unobserved characteristics U_{ip}

$$Y_{ipk}^{*} = X_{ipk}^{'}\beta_j + U_{ipk}, \text{ where } (k = Pd, Sw, Sfi, Iwh) \quad (1)$$

Using the indicator function, the unobserved preferences in equation (1) translate into the observed binary outcome equation for each choice as follow:

$$Y_k = \begin{cases} 1 & if Y_{ipk}^{*} > 0 \\ 0 & Otherwise \end{cases}, \text{ where } (k = Pd, Sw, Sfi, Iwh) \quad (2)$$

Where $k = 1, \ldots., m$ denotes the type of CSA. In equation (1), the assumption is that a rational p^{th} farmer has a latent variable, Y_{ipk}^{*} which captures the unobserved preferences or demand associated with the k^{th} choice of CSA. This latent variable is assumed to be a linear combination of observed characteristics X_{ipk} , both household socioeconomic characteristics and plot characteristics that affect the adoption of k^{th} CSA, as well as unobserved characteristics captured by the stochastic error term U_{ipk}. The vector of parameters to be estimated is denoted by β_j . Given the latent nature of Y_{ipk}^{*} , the estimations are based on observable binary discrete variables Y_{ipk}, which indicate whether or not a farmer undertook a particular CSA on plot ρ.

If adoption of a particular practice is independent of whether or not a farmer adopts another practice (i.e., if the error terms, U_{ipk} are independently and identically distributed with a standard normal distribution), then equations (1) and (2) specify univariate probit models, where information on farmers' adoption of one farming practice does not alter the prediction of the probability that they will adopt another practice. However, if adoption of several farming practices is possible, a more realistic specification is to assume that the error terms in equation (1) jointly follow a multivariate normal (MVN) distribution, with zero conditional mean and variance normalized to unity, where $U_{ipk} \sim MVN(0, \varepsilon)$ and the covariance matrix Ɛ. Hence in this multivariate model, where the adoption of several CSA's are possible, the error terms jointly follow a multivariate normal distribution (MVN) with zero conditional mean and variance normalized to unity (for identification of the parameters) where $U_{Za}, U_{Pd}, U_{Sw}, U_{Sfi}, U_{Iwh}$ and the symmetric covariance matrix Ɛ is given by

$$\Sigma = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} & \rho_{14} & \cdots & \rho_{1m} \\ \rho_{12} & 1 & \rho_{23} & \rho_{24} & \cdots & \rho_{2m} \\ \rho_{13} & \rho_{23} & 1 & \rho_{34} & \cdots & \rho_{3m} \\ \rho_{14} & \rho_{24} & \rho_{34} & 1 & \cdots & \rho_{4m} \\ \vdots & \vdots & \vdots & \vdots & 1 & \rho_{5m} \\ \rho_{1m} & \rho_{2m} & \rho_{3m} & \rho_{4m} & \cdots & 1 \end{bmatrix} \quad (3)$$

Of particular interest are the off-diagonal elements in the covariance matrix, which represent the unobserved correlation between the stochastic components of the different types of CSA's. This assumption means that equation (2) gives MVP model that jointly represents decisions to adopt a particular farming practice or not. This specification with non-zero off-diagonal elements allows for correlation across the error terms of several latent equations, which represent unobserved characteristics that affect the choice of alternative CSA's (Table 1). A likelihood ratio test of the null hypothesis that the correlation coefficients (ρ statistics) are jointly equal to zero against the alternative that ρ does not jointly equal to zero was carried out (Table 1).

Table 1. Correlation coefficient results

	$\boldsymbol{\rho_{Za}}$	$\boldsymbol{\rho_{pd}}$	$\boldsymbol{\rho_{Sw}}$	$\boldsymbol{\rho_{Sfi}}$	$\boldsymbol{\rho_{Iwh}}$
ρ_{Za}	1				
ρ_{pd}	-0.42*** (-0.089)	1			
ρ_{Sw}	-0.83*** (-0.122)	0.55*** (-0.086)	1		
ρ_{Sfi}	-0.38*** (-0.086)	0.65*** (-0.097)	0.55*** (-0.095)	1	
ρ_{Iwh}	-0.24*** (-0.091)	0.36*** (-0.088)	0.32*** (-0.086)	0.29*** (-0.085)	1
Likelihood ratio test of rho21 = rho31 = rho41 = rho51 = rho32 = rho42 = rho52 = rho43 = rho53 = rho54 = 0: chi2(10) = 208.457 Prob> chi2 = 0.0000					

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

The hypothesis of independence between the error terms is strongly rejected, hence the use of MVP as supported by the results. All the technologies under consideration have positive correlations such as Portfolio diversification (Pd), Soil & water conservation (Sw), Soil fertility improvement (Sfi), and Irrigation and water harvesting (Iwh) meaning that the CSA technologies under study do complement each other where they are adopted. The exception is the interaction of zero adaptation with any CSA technology where it indicates negative interaction although practically it is difficult to rule out a mix up in the technologies in the plots of those that indicated zero adaptation.

2. SURVEY METHODOLOGY

2.1 Study Areas

This study was carried out in two districts of Balaka and Nsanje (Fig. 1).The districts were purposively chosen because they are prone to climate variability (droughts and flooding). Balaka District is in the Southern Malawi, located 150 00'S latitude and 350 00'E longitude [Balaka SEP, unpublished].

Nsanje District, on the other hand, is situated at the southern tip of the country within the Lower Shire valley, located 160 45'S latitude and 350 10'E longitude [Nsanje SEP, unpublished].

2.2 Sampling Frame

The study employed a multistage stratified probability sampling frame. Districts were purposively chosen because of being prone to climate variability of droughts and flooding and all traditional authorities were included except one in Nsanje due to accessibility issues. The unit of analysis is the household and therefore the sample frame comprised households from Balaka and Nsanje. Households were also simple randomly selected for the survey which were then stratified into two based on whether they are adopters in CSA technologies (adopters) or non-adopters (non-adopters).

2.3 Sample Size

The sample size was determined following a formula recommended by Krejcie and Morgan [9] as follows;

$$n = \frac{X^2NP(1-P)}{d^2(N-1)+X^2P(1-P)} \tag{4}$$

Where n is the sample size, X^2 is tabulated Chi-Square for 1 degree of freedom at the desirable Confidence level (3.841); N is the population size (N=141839), a summation of Balaka's 65535 farming families, and Nsanje's 76304 (Source; Nsanje and Balaka DADO 2014 reports, unpublished); P is proportion containing the major interest (assumed $P = 0.5$) whereas d is the degree of accuracy presented as a proportion (0.1). The total sample size inclusive of the non-response was 650 households for both Balaka (n=300) and Nsanje (n=350). The study did employ the 60:40 ratio of adopters and non-adopters, with 10% of the calculated sample size used to account for possibilities of non-response [10]. However due to some unforeseeable circumstances such as time limitation, research fatigue by farmers, etc., a total of 619 questionnaires were collected from the two districts (Table 2).

2.4 Data Analysis Techniques

Data were analysed through the generation of descriptive statistics, and the estimation of a multivariate probit (mvp) analysis. The econometric specification in this study examines the determinants of multiple adoption decisions of CSA's, using a multivariate probit model. The MVP approach simultaneously models the influence of the set of explanatory variables on each of the different practices, while allowing for the potential correlation between unobserved disturbances, as well as the relationship between the adoptions of different practices [6]. One source of correlation may be complementarities (positive correlation) and substitutability's (negative correlation) between different practices. Failure to capture unobserved factors

Table 2. Actual sample size per district

District/Farmer type	Nsanje	Balaka	Total
Adopters	219 (+9)	127 (-53)	346 (-44)
Non adopters	130 (-10)	143 (+23)	273 (+13)
Total	349 (-1)	270 (-30)	619 (-31)

Figures in parentheses are deviations to the calculated sample size

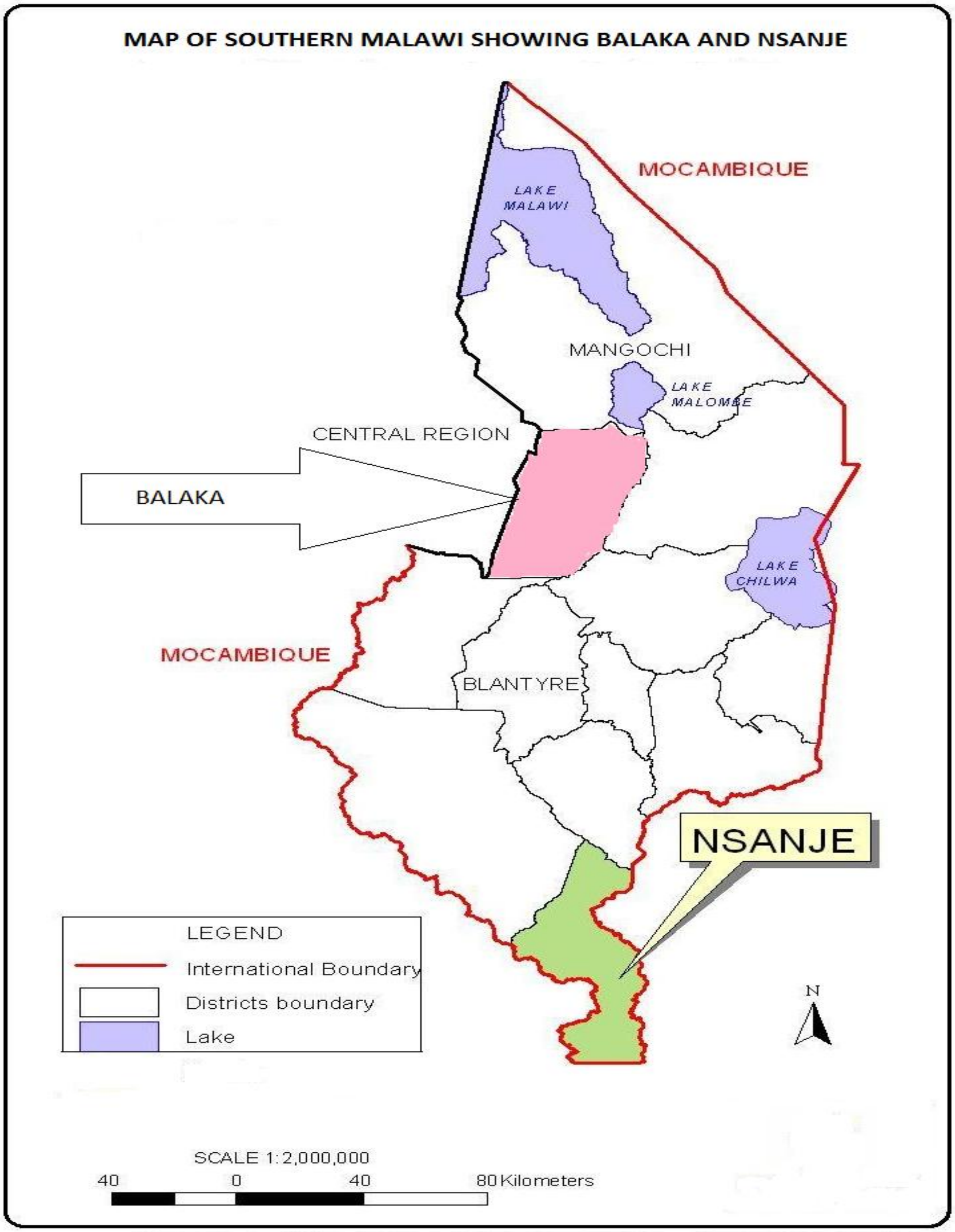

Fig. 1. Map of Southern Malawi

and interrelationships among adoption decisions regarding different practices will lead to bias and inefficient estimates [8]. The data were analysed in STATA version 13 and summarized in Excel 2013.

3. RESULTS AND DISCUSSION

CSA technologies that were considered in this study included portfolio diversification (using improved crop varieties, intercropping, and using different crop varieties that survive in adverse climatic conditions) being practiced by 32% of the respondents, soil and water conservation (mulching, planting of cover crops, minimum tillage operations/conservation agriculture, full tillage operation and digging ridges across slopes in the farm against erosion) done by 42%, soil fertility improvement (agroforestry, applying fertilizer and organic manure) done by 22%, changing planting dates (covering early planting and late planting options) with 17% respondents, and irrigation/rain water harvesting (supplying water to the farm) being practiced by 30% of the respondents.

3.1 Climate Variability in the Districts

The reconnaissance conducted established the reality of climate variability in the two districts and a times series regression run showed trend changes in the amounts of rainfall and temperature (Fig. 2).

3.2 Farmers' Perception of Climate Variability and Impacts

Agricultural production in Malawi is characterized by wide variability in the timing and levels of rainfall, and the increase in temperatures. In addition, crops are subject to various weeds, pests and diseases. To complement the objective climate data presented in Fig. 2, we also present more subjective data from the study, which provides information on how households perceive climate variability, as well as the strategies used to adapt to and mitigate the effect of climate variability. The study showed that farmers from both areas when pooled together were aware of changes in climate variability (99%), which are manifested by great variations in temperature increase (94.5%), reduction in the moisture regime (97.6%), drought (45.8%), flooding (43.7%), untimely rain/ precipitation levels (7.7%) and land degradation (2.8%).

Causes of climate variability were identified to be related to human's social and economic activities on the natural environment in the pursuit of achieving economic objectives at local, regional and/or global levels. Focus group discussions exposed destruction of natural resource base which includes deforestation especially on the hills for charcoal burning and tobacco curing has led to increased formation of rain shadow areas. Population induced environmental degradation resulting from poor farming practices such as burning of vegetative cover, cultivation on marginal land such as hills and marshland and ridging along the slopes in upland areas were also the major cause to climate variability.

The study also reflected discrete farmer's observation on the timeliness, adequacy and distribution of rainfall and the right amount of temperature (heating) to affect the decision that the farmer makes in technology adoption. The study found that about 71.6% of the household were able to follow traditional early warning signs in weather pattern changes and about 65.8% were able to access climate variability information through formal extension services (either Government or Non-governmental organizations) and out of these 44.8% were

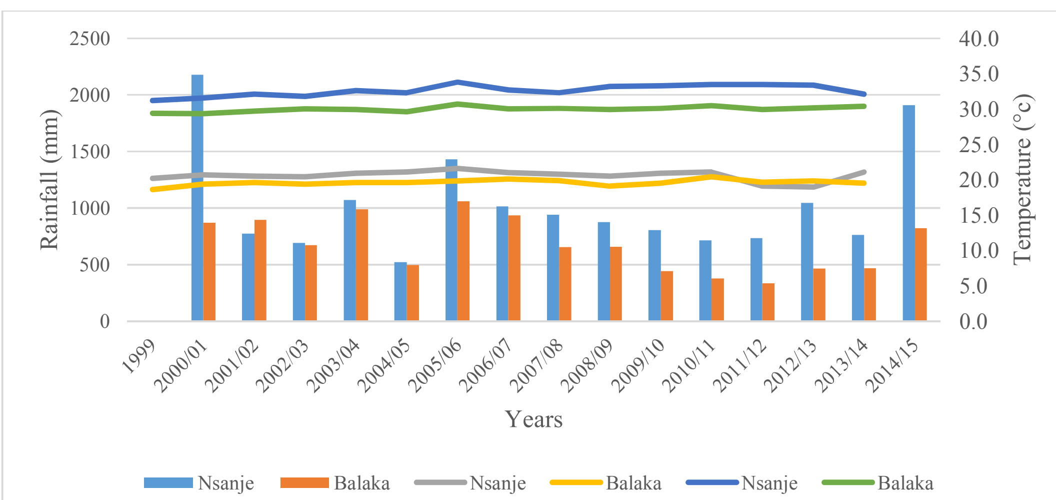

Fig. 2. Minimum and maximum temperatures and rainfall for Nsanje (Long –35.27; Lat - -16.95; 60m above sea level) and Balaka (Long – 34.97; Lat - -14.98; 625 m above sea level)

formally trained in issues pertaining to climate variability. About 89.8% of the households in the pooled sample of the study area reported that they have experienced crop damage, 26.2% of the household reported livestock damage, 27.7% of the household said that the disaster did affect food access in their homes, while 24.5% of the households reported negative effects on income source, while 9.5% household reported occurrence of water borne diseases in their areas. To the extreme 7.2% of the households indicated human death did occur in their households due to the flooding and drought.

3.3 Farmer Adaptation Strategies

Adaptation measures to climate variability can lessen exposure to shocks by preserving soil moisture; aggregating soil organic matter; decreasing soil loss from erosion and flooding; reducing weeds, pest and diseases. Favourable rainfall outcome of up to three months and the right amount of heating (temperatures) is hypothesized to positively impact decisions to adopt certain technologies [11]. On the other hand, unfavourable rainfall outcome and improper levels of heating encourages farmers to adopt CSA technologies. High rainfall does stimulate weed growth and increase water logging [11] together with excessive flooding, which may negatively influence the likelihood of adoption of certain technologies. When faced with climate variability, the study found that farmers have different adaptation measures such using improved variety/early maturing (44.8%), changing cropping calendar (3.5%), changing cropping locations (altitude) (4.5%), irrigating there land (22.6%), increasing the use of fertilizer (both in-organic and organic) (5.7%), shifting from growing crops only to livestock integration or vice versa (2.3%), using improved animal breeds (3.2%), using soil and water conservation techniques (25.6%), having water harvesting technologies (8.2%) and planting trees around and within crops (6.8%). Ironically about 9% of the sampled households did indicate that they don't and they have never adapted to any weather related changes on their farms.

3.4 Soil and Water Conservation Measures

Soil and water conservation practices are done by a bigger proportion of about (25.6%) if the sample is pooled together, which ranges from different techniques such as vertiver grass planting (43.8%), agroforestry (14.5%), box ridges (28.5%), gulley check (4.5%) and planting trees/wood lot (52.2%). According to an article by Ward et.al., 39 percent of registrants in Balaka practiced zero tillage, 86 percent mulched crop residues, and 63 percent practiced either intercropping or crop rotation [12],. Soil and water conservation is meant to reduce soil erosion and improve soil fertility thereby maintaining and enhancing productivity of land. According to government of Malawi, soil conservation technologies for cultivated land in the country has three main objectives: (i) to keep soil healthy and so optimize soil condition for plant growth; (ii) to optimize soil moisture availability for plant growth; and (iii) to keep the soil in place so as to retain soil and nutrients for plant growth [GOM, unpublished].

3.5 Irrigation and Water Harvesting Measures

About 44.1% of the respondents do practice irrigation farming of whom 9.2% households draw their water from boreholes, 14.1% from wells and (17.6%) from rivers. Their major irrigation methods include treadle pump done by (24.8%) households, motor pump (2.1%), drip irrigation (13.1%) and furrow channeling (2.4%). Respondents were also asked to give reasons as to why the majority were not practicing irrigation with such high dry spells. In this regard respondents gave different reasons but the most pronounced were unreliable water source leading to shortage of water (13.1%), lack of equipment (25.2%), shortage of spare parts mainly to treadle pumps 6.7% and lack of chemicals to treat pest diseases on irrigated crops (11.8%).

3.6 Factor Influencing Farmer's Choices of Adaptation Strategies

The MVP model had a likelihood ratio test Wald chi-square (125) = 347.82, P< .001) for independence between the disturbances is robustly rejected, implying correlated binary responses between different CSA's and supporting the use of a MVP model. The results advocate that both socioeconomic and plot characteristics are significant in conditioning the households' decisions to adopt CSA's. The MVP model shows that the probability of adoption of Zero adaptation (Za), Portfolio diversification (Pd), Soil & water conservation (Sw), Soil fertility improvement (Sfi), and Irrigation and water harvesting (Iwh) is more common in the study areas because rainfall is unreliable in relation to timelines, amount, and distribution.

Demographically, there was no differentiation in the age of household head, location of the farmer, whether farmers were monogamous or polygamous married and also there was no gender differences for all the CSA technologies under study related to their adoption (Table 3). These finding is similar with past studies that found no significant difference between male-and female farmer in the adoption of chemical fertilizer and improved seed varieties [13,14]. Literature has cited higher chances of female headed households to be more likely to adopt soil & water conservation relative to male headed households [14]. Whereas most male headed households are less likely to adopt minimum tillage (conservation agriculture), but more likely to adopt irrigation and water harvesting, and soil fertility improvement relative to female headed households [14].

The analysis on farmer type reveals that non-adopters are less likely to go into soil fertility improvement like animal manure application (Table 3), expectations were that, animal manure are cheap and thus more adoption by non-adopters who are relatively poor. However another argument was that soil fertility improvement inform of animal manure application produced by animals owned by mostly adopters who were well off hence lack of manure by non-adopters leads to less adoption. Livestock ownership increased the likelihood of animal manure application for soil improvement [15].

Though with mixed signs farmers' literacy i.e. secondary level education had a positive significant influence on irrigation & water harvesting adoption. This result supports available evidence on the effect of education and extension services on technology adoption [16] [17].

Subsistence farmers had a positive significant influence on the adoption of soil fertility improvement and irrigation & water harvesting but there was a negative influence on portfolio diversification and soil and water conservation technologies (Table 3). Petty trading hada negative adoption effect to all the CSA technologies subjected to MVP with, while formal employment negatively affected adoption of soil fertility improvement technologies.

Land ownership positively influenced adoption of CSA technologies (Table 3), plot characteristics are highly significant variable in determining the choice of agricultural technologies [18]. Farmers are likely to adopt agriculture technologies when they are using owner cultivated plots than on rented in (or borrowed) plots, due to tenure insecurity [16]. The benefits from long- term investments accrues over time, this inter-temporal aspect suggests that secure land access or tenure will impact adoption decisions positively [18]. Farmers prefer using long-term soil fertility enhancements on their own plots, and short-term soil fertility augmentations on rented land or land from relatives. This is consistent with the finding that better tenure security increases the likelihood that farmers can capture the returns from the long term investments without threats of evictions [19].

Famers with large sizes of cultivated plots do likely adopt soil & water conservation and irrigation & water harvesting while those with smaller plots were more into portfolio diversification and soil and fertility improvement (Table 3). Increase in plot sizesmakefarmers to more likely adopt agriculture technologies such as portfolio diversification, soil and water conservation and soil fertility improvement such as use of inorganic fertilizer. This is similar to findings by Pender and Gebremedhin [19], that households that own less land are more likely to adopt portfolio diversification and soil & fertility improvement technologies for a particular plot. Shortage of land as a result of population pressure, makes farmers to intensify agricultural production, using land-saving and yield-augmenting technologies.

Household income and expenditure pattern had a positive effect to soil & water conservation, soil fertility improvement and irrigation & water harvesting with the exception of portfolio diversification. Our results further indicate that household income (proxied by household income and expenditure) seems to favour adoption of the three CSA technologies but not or less likely to portfolio diversification if the decision to adapt is made simultaneously. Perhaps this is because wealthier farmers can afford to adopt expensive and labour intensive technologies such as soil & water conservation, soil fertility improvement and irrigation & water harvesting.

Available institutional arrangements such as traditional early warning system and provision of formal training on climate change (variability) were both positively affecting the adoption of portfolio diversification, soil & water conservation and soil fertility improvement, irrigation & water

Table 3. Multivariate probit (MVP) model regression results

Variables	Portfolio diversification	Soil & water conservation	Soil fertility improvement	Irrigation & water harvesting
Age household head	-0.00589	-0.00410	-0.00400	-0.00222
	(0.00609)	(0.00583)	(0.00637)	(0.00633)
Adopter	1.039***	1.183***	0.806***	0.678***
	(0.161)	(0.148)	(0.171)	(0.162)
Male household head	0.381	-0.208	0.487	-0.371
	(0.279)	(0.259)	(0.310)	(0.287)
Household head educ.	-0.346	0.0908	-0.292	0.456*
	(0.263)	(0.256)	(0.270)	(0.277)
Subsistence farmer	-0.166	-0.0755	0.687***	-0.643***
	(0.175)	(0.170)	(0.201)	(0.178)
Petty trading	-1.045**	-0.388	-0.0164	-1.005**
	(0.464)	(0.355)	(0.469)	(0.402)
Formal employment	-3.978	-4.510	0.539	-4.375
	(136.9)	(138.9)	(0.542)	(148.9)
Size cultivated land	0.0691	0.132*	-0.0236	0.250***
	(0.0647)	(0.0735)	(0.0670)	(0.0888)
Total land	-0.0137	-0.131*	-0.0265	-0.215**
	(0.0552)	(0.0715)	(0.0527)	(0.0898)
Total income	-6.17e-07*	2.72e-07	2.40e-07	2.86e-07
	(3.30e-07)	(2.64e-07)	(2.48e-07)	(2.80e-07)
Household exp.	-3.08e-08	2.70e-08	9.15e-08	7.10e-07*
	(4.21e-07)	(3.85e-07)	(4.30e-07)	(4.03e-07)
Drought	0.0863	0.109	-0.280*	0.410**
	(0.168)	(0.159)	(0.166)	(0.174)
Flooding	0.336**	0.156	0.0135	0.448***
	(0.161)	(0.158)	(0.165)	(0.169)
Traditional EWS	0.163	0.162	0.177	0.288*
	(0.170)	(0.161)	(0.173)	(0.175)
CC formal training	0.206	0.131	0.198	0.393***
	(0.151)	(0.145)	(0.153)	(0.152)
Land from relatives	0.455	-0.102	0.563*	0.0313
	(0.322)	(0.309)	(0.329)	(0.310)
Constant	0.0108	-1.819*	-1.495	-0.835
	(1.069)	(1.071)	(1.034)	(1.057)

*Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

harvesting technology [20]. Acquisition of information about weather and the available new technology to farmers increases the rate of adoption. Important information related to combating climate variability effects upsurge farmers' confidence about a technology's performance hence leading to an individual's change of his/her assessment from purely subjective to objective [20]. Institutional arrangements such as traditional early warning system and provision of formal training on climate variability does increase adoption of agriculture technologies for most hesitant farmers.

Famers that were able to foresee drought had a positive adoption effect on portfolio diversification, soil & water conservation and irrigation & water harvesting while they had a negative adoption effect on soil fertility improvement technologies. Farmers who were able to detect the oncoming flooding had a positive adoption effect on all the CSA technologies under study.

4. CONCLUSION

The study examined socioeconomic factors that influence farming households' behaviour over adaptation strategies by applying a multivariate probit on 619 household in the two district of Nsanje and Balaka in Malawi. This was done to understand the factors in a multivariate model to improve the precision of the estimation results, and also provide consistent standard errors of the estimates enabling an analysis of interrelations between the different adoption decisions.

The results suggest that there is a good level understating among small scale farmers about climate change occurrence and effects in their respective areas. The results are in line with trends of annual mean temperature and rainfall established from climatic data gathered from meteorological stations over the period of 20 also years. Perception results indicate that farmers are making efforts to adapt to climate change in their respective areas. Perception results indicate that farmers perceive that their respective areas are getting warmer and drier over time, and that there are changes in starting, length, intensity and end of rainfall.

A number of important adaptation options being used by small scale farmers in the area were also revealed. Small scale farmers practice strategies such as portfolio diversification (using improved crop varieties, intercropping, and using different crop varieties that survive in adverse climatic conditions), soil and water conservation techniques, soil fertility improvement (agroforestry, applying fertilizer and organic manure) and irrigation/rain water harvesting.

The multivariate probit regression confirmed the role that gender, age, location (either Nsanje or Balaka), farmer type (lead or non-adopter), level of education (primary or secondary level), livelihood status/ off-farm participation (subsistence, petty trader or with formal employment), land size and source/ownership, household income, household expenditure, anticipated weather pattern (whether there will be a drought or a flooding phase), climate variability knowledge/signs (either traditional early warning systems, formal training in climate variability), access to credit, in enhancing farmers' awareness and adopting climate change adaptation measures as they were found to be either positively or negatively determining technology adoption decision.

While adopting irrigation & water harvesting technologies, farm households' decision were positively influenced by farmer type, the level of education (secondary education), size of land being cultivated, household expenditure, the anticipation of disasters such as drought and flooding, presence of traditional early warning system and the farmers being formally trained in climate variability issues; whereas farmers livelihood status/ off-farm participation (subsistence and petty trading) had a negative coefficient towards irrigation & water harvesting technologies.

Furthermore farmer type, off-farm participation, location and gender, given that female headed households are more risk diverse, were likely determinant of CSA technologies such as portfolio diversification, soil & water conservation and soil fertility improvement which were the mostly adopted technologies. Exposure to information about new technologies and early warning system of impeding disasters do significantly affects farmers' choices about what to do on their farms. This information is acquired through informal sources like the media, extension personnel, visits, meetings, and farm organizations and through formal education. It is important that this information should be reliable, consistent and accurate, as the right mix of information properties for a particular technology and impeding disaster is needed.

Combining access to extension, formal education and credit services ensures that farmers have the necessary information for decision making and the means to take up adaptation measures. In order to increase and initiate the likelihood of adopting CSA technologies by smallholder farmers, policy makers should put emphasis on overcoming or increasing other sources of household income either through off farm activities such as credit facilities and petty trading or livestock ownership, secure permanent solutions to irrigation problems, securing land ownership status of farm households and empowering both male and female headed households to be participants and agents of change. The study further revealed that climate variability in form of drought persistence and flooding phases do significantly affect farmers' choice of CSA technology for adaptation.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Tambi NE, Mukhebi WA, Maina WO, Solomon HM. Probit analysis of livestock producers' demand for private veterinary services in the high potential agricultural areas of Kenya. Agricultural Systems. 1999;59:163-176.
2. Rogers EM. Diffusion of innovations. 5th ed. New York: Free Press; 2003.
3. Chebil A, Frija A, Ikafi AB. Irrigation water use efficiency in collective irrigated schemes of Tunisia: Determinants and potential irrigation cost reduction. Agricultural Economic Review. 2012; 13(1):39–48.
4. Dorfamn DJ. Modeling multiple adoption decisions in a joint framework. American Journal of Agricultural Economics. 1996; 78(3):547–57.
5. Marenya PP, Barrett CB. Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in Western Kenya. Food Policy. 2007;32:515–36.
6. Belderbos R, Carree M, Diederen B, Lokshin B, Veugelers R. Heterogeneity in R&D Cooperation Strategies. International Journal of Industrial Organization. 2004; 22(12):37–63.
7. Greene WH. Econometrics analysis. Pearson Prentice Hall, Upper Saddle River. N.J., USA. Open URL; 2008.
8. Teklewold H, Menale K, Bekele S. Adoption of multiple sustainable agricultural practices in Rural Ethiopia. Journal of Agricultural Economics. 2013; 64(3):597-623.
9. Krejcie RV, Morgan DW. Determining sample size for research activities. Educational and Psychological Measurement. 1970;30:607-610.
10. Edriss AK. Pearls of applied statistics. I-Publishers, Toronto, Canada; 2013.
11. Ward PS, Bell AR, Parkhurst GM, Droppelmann K. Tim benton understanding compliance in programs promoting conservation agriculture modeling a case study in Malawi. IFPRI Discussion Paper 01530. Washington DC. International Food Policy Research Institute; 2016.
12. Kassie M, Shiferaw B, Muricho G. Adoption and impact of improved groundnut varieties on rural poverty: Evidence from rural Uganda. Environment for Development Discussion Paper. Environment for Development: Washington, DC, USA. 2010;10–11.
13. Bourdillon M, Hebinck P, Hoddinott J, Kinsey B, Marondo J, Mudege N, Owens T. Assessing the impact of HYV maize in resettlement areas of Zimbabwe; 2002.
14. Doss CR, Morris ML. How does gender affect the adoption of agricultural innovations? The case of improved maize technology in Ghana. Agricultural Economics. 2001;25(1):27–39.
15. Waithaka MM, Thornton PK, Shepherd KD, Ndiwa NN. Factors affecting the use of fertilizers and manure by smallholders: The case of Vihiga, western Kenya. Nutrient Cycling in Agro Ecosystems. 2007;78:211–224.
16. Freeman AH, Owiti JM. Fertilizer use in semi-arid areas of Kenya: Analysis of smallholder farmer's adoption behavior under liberalized markets. Nutrient Cycling in Agro ecosystems. 2003;66:23–31.
17. Chirwa EW. Adoption of fertilizer and hybrid seeds by smallholder maize farmers in southern Malawi. Development Southern Africa. 2005;22(1): 1–12.
18. Kassie M, Holden ST. Sharecropping Efficiency in Ethiopia: Threats of eviction and kinship. Agricultural Economics. 2007; 37:179–88.
19. Pender J, Gebremedhin B. Determinants of agricultural and land management practices and impacts on crop production

and household income in the highlands of Tigray, Ethiopia. Journal of African Economies. 2007;17:395–450.

20. Caswell M, Fuglie K, Ingram C, Jans S, Kascak C. Adoption of agricultural production practices: Lessons learned from the US. Department of Agriculture area studies project. Washington DC. US Department of Agriculture. Resource Economics Division, Economic Research service, Agriculture Economic Report No. 792; 2001.

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