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Determinants of adoption of multiple climate change adaptation strategies in Southern Malawi: An ordered probit analysis

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This paper aimed to identify factors affecting adoption of multiple climate change adaptation strategies in Southern Malawi. An ordered probit model was estimated using survey data collected in Nsanje and Balaka districts in 2014-2015 cropping season. Age of household head, total land area owned, petty trading and formal employment were found to reduce the probability of adopting more than two CSA strategies. Farmers who reported observing changes in moisture levels in their areas for the 20-year period prior to the survey were found to have lower probability of adopting four CSA strategies as compared to those who reported not observing any changes in moisture in the same time period. Importantly, being a lead farmer, which proxied ample access to climate smart agriculture extension messages and training access, acreage used in agricultural production and observing an increase in incidences of floods in a 20-year period prior to this study increased the probability of adopting more than two CSA strategies. Interestingly, household income was found not to affect number of CSA strategies adopted. The study recommends that relevant stakeholders should provide farmers with CSA-related extension messages if more farmers are to adopt multiple CSA techniques.

Key words: Climate-smart agriculture, adoption, marginal effects, probability, ordered probit.

INTRODUCTION

Impacts of climate-related shocks on agricultural systems have put building resilient systems to the forefront of agricultural policies globally. Of late, policymakers and development practitioners have increased interest in getting as many farmers as possible to adopt sustainable production practices that strengthen agricultural systems. Among a multiplicity of strategies that are being used to mitigate the agricultural impacts of climate change, the so called Climate Smart Agriculture (CSA) practices that help sustainably increase agricultural productivity; adapt and building resilience of agricultural and food security systems and reduce greenhouse gas emissions from

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agriculture (FAO, 2013) have shown much promise. The interesting work that has now been left for researchers is to inform policymakers on the determinants of adoption of these CSA practices so as to enable them enact practicable strategies that will see farmers adopt the aforementioned practices.

Fortunately, a considerably large number of empirical research has been conducted over the years to understand factors that affect farmer adoption of Climate-Smart Agriculture (Teklewold et al., 2013; Wollni et al., 2010; Nyong et al., 2007). However, a vast majority of the current research has only focused on assessing the determinants of one CSA strategy, albeit CSA is a package of practices that is adopted by farmers in various combinations (Pannell et al., 2014; Teklewold et al., 2013). Indeed, farmers enjoy a variety of benefits by adopting multiple strategies as some of the strategies are complements and substitutes (Teklewold et al., 2013). Therefore, adopting multiple CSA techniques help build a sustainable agricultural production systems well resilient to climate-related and other shocks. Currently, no research has been conducted in Malawi that informs policymakers on determinants of adoption of such a multiplicity of CSA technologies. This paper, therefore, tries to close this information gap by assessing the determinants of smallholder farmer adoption of several CSA strategies using data collected from farmers from Balaka and Nsanje districts in Southern Malawi.

In this paper, the authors have considered smallholder adoption of soil and water conservation, soil fertility improvement, irrigation and water harvesting as well as farm enterprise (portfolio) diversification since they are the main CSA strategies that are practiced in the study area. Following Teklewold et al. (2013), Wollni et al. (2010) as well as D'Souza et al. (1993), we have used the number of these CSA practices that a household practices as a measure for level of adoption of CSA practices which we have fitted as the regressand in an ordered probit model. Greene (2008), Teklewold et al. (2013) and Wollni et al. (2010) noted that as opposed to Poisson models that assume equal probability of adoption for all CSA technologies, in reality, adoption of the second or more technologies are conditioned by adoption of the first technology. This then supports our use of ordered probit as the ordering of the response variable allows us to explicitly incorporate the experience that the farmer has obtained from practicing the first technology.

The model results indicate that the probability of adoption of more than two strategies was negatively affected by age of household head, total land area owned, petty trading and formal employment were found to reduce the probability of adopting more than two CSA strategies. Farmers who reported observing changes in moisture levels in their areas for the 20-year period prior to the survey were found to have lower probability of adopting four CSA strategies as compared to those who reported not observing any changes in moisture in the same time period. Paradoxically, household income was found not to affect number of CSA strategies adopted. Overall, this study contributes to the understanding of factors affecting adoption of subpackages of CSA.

METHODOLOGY

Study description

The study focused on technology adoption as a choice over four practices involving 1) portfolio diversification, 2) soil and water conservation, 3) soil fertility improvement, 4) irrigation/rain water harvesting and our control were farmers in zero or no adaptation category (Table 1).

Sampling and data

Data used in the study were collected in 2014-15 cropping season from households using a semi-structured questionnaire. The study employed multistage sampling whereby Nsanje and Balaka districts in southern Malawi were purposely selected due to their vulnerability to climate related disasters like droughts and floods and the need to find strategies that can make households in the districts more resilient to climate-related shocks. Within a district, traditional authorities were randomly selected. Villages within each traditional authority were then randomly selected. Households that were interviewed were obtained using simple randomly sampling from the selected villages. The sample size was determined following a formula recommended by Krejcie and Morgan (1970) as follows;

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

Where n is the sample size, χ^2 is tabulated Chi-Square for a one degree of freedom at the desirable confidence level (3.841); N is the population size; P is proportion of adopters (assumed P=0.5 to obtain maximum sample size as the true population P was not known), whereas d is the degree of accuracy presented as a proportion (0.1). Ten percent of the calculated sample size was used to account for possibilities of non-response.

Analytical framework

The decision to adopt climate change adaptation technologies is largely conditioned by farmer's perception of the benefits that will accrue to them once they adopt a technology against perceived costs and risks associated with the technologies (Wollni et al., 2010). Therefore, in adopting climate smart agriculture technologies, the farmer tries to maximize some utility function while minimizing costs in a Marshallian demand framework. There are possibilities, however, that the utility maximizing solution can be one or multiple CSA technologies that a farmer may choose to adopt.

Climate Smart Agriculture is generally a complex system that

Table 1. Definitions of CSA technologies under study.

CSA technology	As defined in this study
Portfolio diversification	Using improved crop varieties, intercropping, different crop varieties that survive in adverse climatic conditions
Soil and water conservation	Farmers' use of mulching, planting of cover crops, minimum tillage operations (conservation agriculture), full tillage operation and digging ridges across slopes
Soil fertility improvement	Agroforestry, applying fertilizer and organic manure
Irrigation/rain water harvesting	Involving storage and supplying water to the farm
No / zero adaptation	Farmers not using any adaptation method to counteract the negative impact of climate variability

involves different technologies and soil management practices (Wollni et al., 2010). Farmers may adopt one or many of these technologies depending on their preference (Teklewold et al., 2013). The main analytical challenge that emanates from adopting multiple technologies in various combinations is connected to defining a cutoff point between adopters and non-adopters. Practically, a majority of farmers just adopt a number of adaption strategies and not others. This then makes it possible for us to handle the aforementioned challenge by using the number of CSA technologies as the dependent variable for our Ordered Probit model, noting the ordinal nature of the response variable (Teklewold et al., 2013; Wollni et al., 2010; Boz and Akbay, 2004). Given that the dependent variable is count in nature, it is normal to think about Poisson regression models. However, as Greene (2008), Teklewold et al. (2013) and Wollni et al. (2010) noted, Poisson models assumed equal probability of adoption for all CSA technologies, whereas in reality, adoption of the second or more technologies are conditioned by adoption of the first technology. This then supports the use of ordered probit as the natural ordering of the response variable allows us to explicitly incorporate the experience that the farmer has obtained from practicing the first technology.

As alluded to the above, the authors have analyzed the model in a random utility framework. The response variable represents the number of CSA technologies that the farmer has adopted. It shows us whether a farmer has adopted zero $\left(\omega_i = 0\right)$, one $\left(\omega_i = 1\right)$, two $\left(\omega_i = 2\right)$, three $\left(\omega_i = 3\right)$ or four $\left(\omega_i = 4\right)$ various technologies. It is assumed that farmers choose to adopt the number of CSA practices so as to maximize the following underlying utility function:

$$U_i = V_i(\beta x_i) + u_i \text{ for } i = 1, ..., n$$

Where V_i, which is the observed part of the utility function, is a function of a vector of exogenous household, plot and institution-related variables, x_i , and a vector of parameters to be estimated, β, and is assumed to be equivalent to the mean of the random variable U_i (Wollni et al., 2010). Further, it is assumed that the unobserved part of utility function is represented by i.i.d random error term u_i with mean of zero (Greene, 2008). Therefore, the farmer adopts an additional technology if the utility they obtain from adopting it is greater that the utility they obtain if they do not adopt the additional technology (Wollni et al., 2010; Daykin and Moffat, 2002). According to Daykin and Moffat (2002), the utility U_i of each individual farmer is not observed; however, it was observed that:

$$\omega_i = 1 \text{ if } U_i \leq \alpha_1$$
$$\omega_i = 2 \text{ if } \alpha_1 \prec U_i \leq \alpha_2$$
$$\omega_i = 3 \text{ if } \alpha_2 \prec U_i \leq \alpha_3$$
$$\omega_i = 4 \text{ if } \alpha_3 \prec U_i \leq \alpha_4$$

Where $\alpha_1 \prec \alpha_2 \prec \alpha_3 \prec \alpha_4$ are "cutoff or threshold" parameters that are estimated using β. Daykin and Moffat (2002) posited that β does not contain intercept term as the term is normalized to zero to allow the threshold parameters to be "free" parameters. Alternatively, Greene (2008) suggested that one of the threshold parameters can simply be normalized.

We have followed Wollni et al. (2010) and Daykin and Moffat (2002) in assuming that u_i is normally distributed such that we can actually get the following probabilities:

$$\begin{aligned}
&prob(\omega = 0 \mid x) = \text{prob}(\text{U} \leq \alpha_1 \mid \text{x}) \\
&= prob(\beta'\text{x} + \text{u} \leq \alpha_1 \mid \text{x}) = \Phi(\alpha_i - \beta'\text{x}), \\
&prob(\omega = 1 \mid x) = \Phi(\alpha_2 - \beta'\text{x}) - \Phi(\alpha_1 - \beta'\text{x}), \\
&prob(\omega = 2 \mid x) = \Phi(\alpha_3 - \beta'\text{x}) - \Phi(\alpha_2 - \beta'\text{x}), \\
&prob(\omega = 3 \mid x) = \Phi(\alpha_4 - \beta'\text{x}) - \Phi(\alpha_3 - \beta'\text{x}), \\
&prob(\omega = 4 \mid x) = 1 - \Phi(\alpha_4 - \beta'\text{x})
\end{aligned}$$

Where $\Phi(\bullet)$ is the standard normal cumulative distribution function. The parameters α and β are estimated by the following log-likelihood function:

$$L = \sum_{i=1}^{n} \sum_{\omega=i}^{i} \log\left(\Phi\left(\alpha_i - \beta' x\right) - \Phi\left(\alpha_1 - \beta' x\right)\right).$$

We have used the oprobit command in Stata version 13.0 to estimate the ordered probit model. Thereafter, marginal effects were calculated to determine the magnitude by which each independent variable alter the likelihood of respondents in each of the five categories of the response variable. According to Chen et al. (2002) and Liao (1994), marginal effects for ordered probit model can be obtained as:

$$\frac{\delta(\omega_i = j)}{\delta x_n} = \left[\Phi\left[\alpha_{j-1} - \sum_{\alpha-1}^{\alpha}\beta_n x_n\right] - \Phi\left[\alpha_j - \sum_{\alpha-1}^{\alpha}\beta_n x_n\right]\right]\beta_n$$

And j is the number of CSA technologies that a farmer is practicing.

RESULTS AND DISCUSSION

Characteristics of the farm households

Out of the 428 farmers sampled, 39.9% reported that they were not using any CSA strategy in their agricultural production, whereas 17.9, 15.3, 28.3 and 4.3% of the farmers reported that they had adopted one, two, three and four CSA practices, respectively. Overall, there seems to be a problem with CSA extension service availability in the study area as only 32.4% of the farmers reported to have accessed climate smart agriculture related extension services, 12 months preceding this survey.

Mean age of household heads was 44.6. Analysis of variance shows that there are no differences in ages between and among farmers who reported to have adopted various numbers of CSA technologies (Prob>F= 0.4120). A majority of household heads (62.2%) reported to have obtained some primary level education while 26.7% of the heads reported to have attended secondary school with 10% reporting to have no formal education at all.

On average, households had a mean annual income of MK223, 257.00 (US$465.12 at 2013 exchange rate). One way analysis of variance shows that there are no differences in total household incomes among and within farm households that adopted various numbers of CSA practices (Prob>F=0.2544).

Farmers in the study area seem to cultivate small pieces of land (mean area cultivated in 2012/13 was 2.0 acres). No significant differences were found in acreage cultivated in the sample among smallholder farmers who adopted various climate smart agriculture techniques.

Adoption of the technologies

As aforementioned, the CSA strategies considered in this study are portfolio diversification, soil and water conservation, soil fertility improvement as well as irrigation and water harvesting techniques. From these four CSA strategies, we can obtain 24 various combinations of CSA strategies that farmers may adopt; each with its own determinants and probability of adoption.

At individual CSA strategy level, however, 35% of the respondents reported to have adopted portfolio diversification, 43.7% practiced soil and water conservation, 24.2% of the sample reported that they practiced soil fertility improvement while 31% said they practiced irrigation and water harvesting.

Generally, levels of adoption are low in the sample for all CSA strategies. Soil and water conservation is the most adopted CSA strategy with 44% of the farmers reporting to have adopted it. This may be the case because a lot of extension messages on CSA issues hover around soil and water conservation. The frequency distribution of the number of CSA technologies that farmers reported to have adopted in study area are presented in Figure 1.

Determinants of CSA technologies adoption

The model's Chi square coefficient (165.17 with 27° of freedom) is statistically significant at 1% level of probability (P<0.0001). All the threshold parameters are significant; implying natural ordering of the response variable (α_1 , α_2 and α_3 are significant at 5% level of probability whereas α_4 is significant at 1% level of significance). Wollni et al. (2010) posit that the coefficient estimates of the ordered probit model are not easily interpretable. Instead, they did recommend to concentrate on the marginal effects after estimating the ordered probit model. To understand how each independent variable changes the probability of adopting the number of CSA technologies given the covariates, an increase in age of the household head reduces the probability of adoption of more than two CSA practices by 4.5% (Table 2). This is in agreement with what Teklewold et al. (2013) found in Ethiopia. An increase in age of the household head was speculated to reduce the probability of adopting more than two CSA technologies, because as farmers advance in age, they tend to minimize activities that demand much of their labour and management skills. Further, due to experience with climate-related shocks over years, older farmers acquire indigenous knowledge that allow them to be relatively resilient to shocks than younger farmers such that they find it convenient to rely on their indigenous knowledge than adopt modern practices that may have steep learning curves (Nyong et al., 2007).

Holding all factors constant, an acre increase in area of total land owned reduces the probability of adopting more than two CSA practices by 11% (Table 2). Generally, increasing the area that a typical smallholder farmer controls would entail introducing additional costs to the

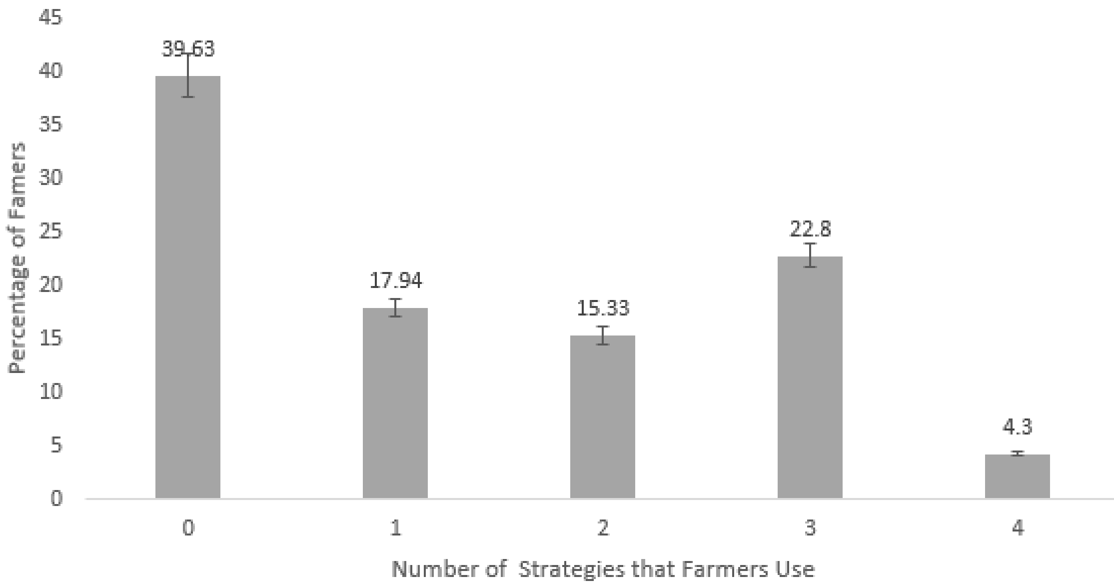

Figure 1. Percentage of farmers adopting various numbers of CSA practices.

farmer which they may fail to cover given their resource base. The probability of adopting more than two CSA strategies has a 15% increase for every additional acre. This result makes sense when one considers how resource constrained smallholder farmers are to manage a lot of climate-smart technologies on a bigger plot of land.

The status of being a lead farmer[1] was used as a proxy for ample access to CSA extension messages given that most Non-Governmental Organizations (NGOs) in the study area are training and using lead farmers to drive adoption of CSA practices. As expected, the marginal effects show that being a lead farmer, as opposed to being regular/follower farmer, increases the probability of adopting more than two CSA practices by 36% (Table 2). This result implies that ample access to extension services can help get many farmers adopt a mix of CSA technologies that can make their agricultural production system more resilient and sustainable.

For those who reported not being employed during the survey, being a petty trader increases and being formally employed reduces the probability of adopting more than two CSA strategies by 21 and 34%, respectively (Table 2). Although, not expected, these results make sense because farmers who have diversified their income generating activities are generally more able to handle impacts of climate-related agricultural production shocks through purchasing food, using other means, and no need to make their agricultural production more resilient. Most farmers who are involved in off farm income generating activities rarely attend CSA extension activities and this affects their probability of adopting the CSA strategies.

Farmers who observed an increase in floods in a 20 years period preceding the survey had 9% higher probability of adopting more than two climate-smart agriculture practices than those who reported not observing any increase in frequency of floods in the said 20 years period (Table 2). These were expected results given that, it is only those farmers who appreciate the risk that floods pose to their agricultural enterprise that see the need to adopt CSA practices to make them more resilient to the shocks.

Farmers who reported observing changes in moisture levels in their area during a 20year period before the survey had a 19% lower probability of adopting four CSA technologies. A positive relationship was expected between observing changes in moisture levels in the farmer's area with adoption of higher numbers of CSA practices, given the importance of moisture in agricultural production. However, the marginal effects show otherwise.

A positive and significant relationship between household income and intensity of adoption of technologies was expected, literature suggests that household income is an important driver of adoption (Katengeza et al., 2012; Wollni et al., 2010; Boz and Akbay, 2004). It was expected that higher-income households were supposed to have higher probabilities of adopting more than one CSA technology given their potential to purchase inputs that may help sustain many CSA technologies as compared to lower-income

[1] Farmers who are supported by extension service providers and NGO to provide agricultural extension services to other farmers in their communities (Franzel and Simpson, No Date)

Table 2. Ordered probit results with marginal effects.

Variables	Coefficients	Marginal effects				
		Prob(Y=0|X) dy/dx	**Prob(Y=1|X) dy/dx**	**Prob(Y=2|X) dy/dx**	**Prob(Y=3|X) dy/dx**	**Prob(Y=4|X) dy/dx**
Age of household head	-0.130** (0.0597)	.0489***	-0.005*	0.001	-0.012**	-0.032***
Age of household head square	1.646** (0.800)	-0.620***	0.065*	-0.014	0.153**	0.416***
Log of land area	-0.263* (0.145)	0.099*	-0.010*	0.002	-0.024*	-0.066*
Farmer type (lead farmer=1)	1.142*** (0.139)	-0.422***	0.042***	0.017	0.105***	0.256***
Polygamous married	0.385 (0.349)	-0.134	0.022	-0.017	0.025*	0.104
Smallholder farmer(yes=1)	-0.154 (0.141)	0.057	-0.006	0.002	-0.013	-0.035
Petty trader (yes=1)	-0.658** (0.285)	0.257**	-0.014***	-0.035	-0.075**	-0.132***
Formally employed (yes=1)	-1.409** (0.682)	0.493***	-0.0166***	-0.136	-0.149***	-0.191***
Household dependency ratio	0.0344 (0.0415)	-0.012	0.001	-0.0003	0.003	0.008
Log of land area used	0.429*** (0.143)	-0.161***	0.016**	-0.003	0.039***	0.108***
Observed change in moisture over past 20 years(yes=1)	-0.701* (0.387)	0.220**	- 0.056	0.052	-0.024	-0.19*
Observed increase in floods over past 20 years(yes=1)	0.270* (0.141)	-0.101*	0.011*	-0.003	0.024*	0.068*
Access agricultural extension(yes=1)	0.153 (0.134)	-0.0580852	0.005	-0.0003	0.014	0.037
Received climate change training	0.106 (0.130)	-0.0399444	0.004	-0.0009541	0.009	0.026
α_1			5.546** (2.669)			
α_2			6.142** (2.666)			
α_3			6.670** (2.667)			
α_4			8.032*** (2.675)			
Observations			420			
Wald chi2(27)			165.17			
Prob > chi2			0.0000			
Log pseudolikelihood			-520.22665			
Pseudo R2			0.1406			

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Marginal effects (dy/dx) calculated at the mean for continuous variables and for a discrete change from 0 to 1 for dummy variables.

households. However, this study shows that household income does not significantly affect adoption of multiple CSA practices.

CONCLUSIONS AND POLICY RECOMMENDATIONS

This paper has analyzed the determinants of multiple adoption of climate smart agricultural practices in Balaka and Nsanje districts using an ordered probit model. The results indicate that age of household head, total area of land that a household owns, being involved in petty trading and formal employment as opposed to being unemployed reduce the probability of adoption of more than two CSA strategies. Unexpectedly, it was found that farmers who reported having observed changes in moisture levels in their areas for the 20-year period prior to the survey have a lower probability of adopting four CSA strategies as compared to those who reported not observing any changes in moisture in the same time period and area.

Most importantly, the study found that being a lead farmer, which proxied ample access to climate smart agriculture extension message and training access, acreage used in agricultural production in the year preceding our survey as well as observing an increase in incidences of floods in a 20-year period prior to our study increased the probability of adopting more than two CSA strategies. Interestingly, being in polygamous marriage contract was found to increase adoption of three CSA strategies.

However, it is worth noting that the ordered probit model and the resultant calculation of marginal effects indicate that none of the socioeconomic and institutional factors that conceptually affect the number of climate smart agriculture strategies that the farmers adopt significantly affects the probability of adopting two CSA strategies. Further, the study has shown that household income does not significantly affect the adoption of multiple CSA strategies, contrary to this study expectation.

Based on the results of this study, it is recommended that all relevant stakeholders should strive to provide smallholder farmers with climate smart agriculture-related extension messages if more farmers are to adopt many CSA techniques that will make their agricultural production systems resilient to climate change.

Conflict of Interests

The authors of the study and sponsors do not have any vested interest in the findings of the study.

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REFERENCES

Boz I, Akbay C (2004). Factors influencing the adoption of maize in Kahramanmaras province of Turkey. Agric. Econ. 33:431-440.

Chen K, Ali M, Veeman M, Unterschultz J, Le T (2002). Relative Importance Rankings for Pork Attributes by Asian-Origin Consumers in California: Applying an Ordered Probit Model to a Choice-Based Sample. J. Agric. Appl. Econ. 34(1):67-79.

Daykin A, Moffat PG (2002). Analyzing Ordered Responses: A Review of the Ordered Probit Model. Underst. Stat. 1:157-166.

D'Souza G, Cyphers D, Phipps T (1993). Factors Affecting the Adoption of Sustainable Agricultural Practices. Agric. Resour. Econ. Rev. 22:159-165.

FAO (2013). Climate-Smart Agriculture Sourcebook. Rome: FAO. Retrieved March 2, 2016, from Food and Agriculture Organization of the United Nations: http://www.fao.org/docrep/018/i3325e/i3325e.pdf

Franzel S, Simpson B (No Date). Farmer to Farmer Extension Approaches. Retrieved March 2, 2016, from Mordenizing Extension and Advisory Services: http://www.meas-extension.org/meas-offers/program-evaluation/farmer-to-farmer

Greene WH (2008). Econometric Analysis (Sixth ed.). New Jersey: Pearson Prentice Hall. Retrieved February 28, 2016.

Katengeza SP, Mangisoni JH, Kassie GT, Sutcliffe C, Langyintuo A, La Rovere R, Mwangi W (2012). Drivers of improved maize variety adoption in drought prone areas of Malawi. J. Dev. Agric. Econ. pp. 393-403.

Krejcie RV, Morgan DW (1970). Determining Sample Size for Research Activities. Educ. Psychol. Measure. 30:607-610.

Liao TF (1994). Interpreting Probability Models: Logit, Probit, and Other Generalized Linear Models (Quantitative Applications in the Social Sciences). California, United States of America: SAGE Publications, Inc.

Nyong A, Adesina F, Elasha BO (2007). The value of indigenous knowledge in climate change mitigation and adaptation strategies in the African Sahel. Mitig. Adapt. Strat. Glob. Change 12:787-797.

Pannell DJ, Llewellyn RS, Corbeels M (2014). The farm-level economics of conservation agriculture for resource-poor farmers. Agric. Ecosyst. Environ. 187:52-64.

Teklewold H, Kassie M, Shiferaw B (2013). Adoption of Multiple Sustainable Agricultural Practices in Rural Ethiopia. J. Agric. Econ. 64(3):597-623.

Wollni M, Lee DR, Thies JE (2010). Conservation agriculture, organic marketing, and collective action in the Honduran hillsides. Agric. Econ. 41:373-384.