Journal of Economics and Sustainable Development www.iiste.org
ISSN 2222-1700 (Paper) ISSN 2222-2855 (Online)
Vol.7, No.2, 2016

Climate Variability and Farm Technology Adoption Decisions among Smallholder Farmers in Pangani River Basin

Arbogast Moshi[1*] Joseph Hella[2] Aida Isinika[3]
1. PhD Candidate at Department of Agricultural Economics and Agribusiness, Sokoine University of Agriculture, P.O.Box, 3007, Morogoro, Tanzania
2. Department of Agriculture Economics and Agribusiness, Sokoine University of Agriculture, P.O.Box 3007, Morogoro, Tanzania
3. Institute of Continuing Education, Sokoine University of Agriculture, P. O. Box 3007, Morogoro, Tanzania

The research is financed by Climate Change Impacts Adaptation and Mitigation (CCIAM) in Tanzania

Abstract
Climate change is currently a serious threat for agriculture development and food security in sub-Saharan Africa. With the Intergovernmental Panel on Climate Change (IPCC) climate outlook for the 21st century, the future of maize production in Tanzania remains under threat due to more intense and frequent droughts, and more erratic rainfall patterns. Effective adaptation to these ongoing changes in climatic condition is key to securing food production and livelihoods for millions of poor people. This paper analyzes factors that facilitate or impede the probability and level of adoption of sustainable farm technologies and farm households in response to climate shocks. A multivariate probit model was applied to the model the adoption decisions by farm households facing multiple farm technologies which can be adopted in various combinations. The analysis shows that both the probability and the level of decisions to adopt farm technologies influenced by rainfall and plot-level disturbances, household wealth, institutional factors, distance to the farm plot and input market. The results further show that there were complementarities between farm technologies which are not yet sufficiently exploited. In the light of these findings, government policies, and strategic investment plans should ensure the provision of improved farmer education to generate greater awareness about the multiple benefits of sustainable agricultural practices in the fight against climate change and variability.
Keywords: Climate change, Technology adoption, Multivariate probit

1. Introduction

1.1 Background Information

Climate change and more extreme weather patterns are already being experienced as it is evident in in the form of severe negative impacts on food production, food security and natural resources all over the globe (IPCC, 2013). Sub-Saharan Africa has been portrayed as the most vulnerable region towards the impacts of global climate change because of its reliance on agriculture which is highly sensitive to weather and climate variables such as temperature, precipitation and extreme events. Africa also has low capacity for adaptation (Hertel *et al.,* 2010).Tanzania is already affected by climatic variability and extreme weather events. Studies already show dim figures indicating continuing failure in agricultural productivity in Tanzania resulting from climate change and variability (URT, 2002). These projections raise serious concerns about agricultural development in Tanzania which has been a key driver of economic development ensuring food security and generating rural incomes as well as foreign exchange earnings. Noticeable effects of climate change have been observed Pangani river basin that is located in the Northeastern part of Tanzania. Incidences of crop failures in the basin occur quite frequently due to erratic rainfall leading to low agricultural productivity (Mtalo *et al.,* 2010).

Declining agricultural productivity and volatility associated with climate change, deepens the risk of food insecurity in Tanzania. Given the limited scope for land expansion in the basin (IUCN, 2009), productivity-led growth is the only feasible option for improving production of food crops in the long run especially maize which is the main staple crop but also the main source of cash income for most small holder farmers. Increasing maize productivity will ensure long-term food security and greater contribution to poverty reduction. Given that agricultural production remains the main source of income for most rural communities, adaptation of the agricultural sector to the adverse effects of climate change is imperative for protecting and improving the livelihoods of the rural poor in Pangani River Basin.

Various organizations such as Food and Agricultural Organization (FAO) policies and other development partners are promoting sustainable agricultural practices as a means of adapting to and mitigating climate change. These practices broadly defined include legume intercropping, improved crop varieties, the use of animal manure, use of inorganic fertilizers, and soil and water conservation (Kassie *et al.,* 2010; Wollni *et al.,* 2010). Notwithstanding their benefits, the adoption rate of these technologies and practices is still low in rural areas of developing countries (Kassie *et al.,* 2009), despite a number of national and international initiatives to encourage farmers to invest in them. The same is true in Tanzania, where, despite accelerated crop failures and considerable efforts to promote various farm production technologies, the adoption of many recommended measures is minimal (Nkonya *et al*, 1997; Esfaw *et al.,* 2010). One question that arises is whether these practices are actually effective adaptation strategies in the specific circumstances of Tanzanian farmers. A second question is how household and system-level adaptive capacity, or lack thereof, affects the selection of farm practices. In an attempt to answer these questions the objectives of the paper are: to analyze the adoption pattern of sustainable agricultural practices in different hydrological conditions in the Pangani River Basin; to find out the important factors influencing adoption; and to test the hypotheses that spread of sustainable farm management practices is equal across the basin.

2. Theoretical Framework

When it comes to the adoption of a new technology, farmers are faced with choices and tradeoffs. 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 (De Janvry *et al.,* 2010). It follows that some farmers adopt the new technology while others do not. In such a context, farmers' decisions regarding the adoption of farm technology can be explained using the theory of maximizing the expected utility function subject to budget, access to information, credit and the availability of both the technology and other inputs. Following this theory, farmers adopt a given new technology if the expected utility obtained from the technology exceeds that of the old one (Kahneman and Tversky, 1979; Smale *et al.,* 1994). Farmers are also more likely to adopt a mix of measures to deal with a multitude of agricultural production constraints than adopting a single practice (Knowler, and Bradshaw, 2007). In this context, recent empirical studies of technology adoption decisions assume that farmers consider a set of possible technologies and choose the particular technology bundle that maximizes the expected utility accounting for interdependent and simultaneous adoption decisions (Teklewold *et al*., 2013; Asfaw *et al.,* 2014).

The main shortcoming of most of the previous studies of farm technology adoption is that they assume a single technology without considering the possible correlation or interdependence between different technologies (Yu *et al.,* 2008), thereby masking the reality that decision makers are often faced by a set of choices. Recent empirical studies (Kassie *et al.,* 2009; 2013) argued that farmers in Sub-Saharan Africa usually consider a set of possible technologies and select the combination they assume will have the best results. In general, when technologies are correlated, univariate modeling excludes useful information contained in the interdependence and adoption decision analysis (De Janvry *et al.,* 2010). Univariate models ignore the potential correlation among unobserved disturbances in the adoption equations (Wooldridge, 2002; Greene, 2003). In this context, the current study employs a multivariate probit (MVP) econometric technique, which simultaneously models the influence of the set of explanatory variables on each of the different practices, while allowing the unobserved and unmeasured factors (error terms) to be freely correlated (Lin *et al.,* 2005).

3.0 Methodology

3.1 Study Area and Sampling Procedure

The study was conducted in Pangani River Basin, located in the North Eastern part of Tanzania. The basin has a total catchment area of about 43,650 square kilometer with about 8%the area lying in Kenya (IUCN, 2003). In Tanzania the basin falls under four administrative Regions of Manyara, Arusha, Kilimanjaro and Tanga (PBWO, 2010).The basin is currently home to about 6.8 million inhabitants (URT, 2013). Ninety percent of this population lives in the highlands where the population density is up to 300 people per sq. km, compared to 65 people per square kilometer in the lowlands (IUCN, 2009). The national aggregate population is 51 people per square kilometer (URT, 2013). Such rapid population growth and high population density in Pangani river basin, coupled with climate change is posing pressure to the basin's natural resources. The basin has been divided into three rainfall patterns namely: high rainfall (>1200), moderate rainfall (700-1200mm) and low rainfall (<700 mm) (Ndomba, 2010). Most of the food and cash crops are produced under rain fed agriculture (Mtalo *et al.,* 2010). Maize is the most common crop grown by most small holder farmers throughout the Basin (IUCN, 2009). Erratic and significantly delayed short and long rains have affected production of maize in the basin, resulting into food shortages (Welling *et al.,* 2011).

3.2 Analytical Model

In the case of adopting farm technology induced by climate change shock, farmers are faced with choices and tradeoffs. Differences in adoption decisions are often due to the fact that farmers have different adaptive capacity, different objectives, preferences, and different socio-economic and biophysical characteristics (Yu *et al.,* 2008). In such a context, farmers' decisions regarding the adoption of innovations can be explained using the theory which guides 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.In the first step, a shock-affected household decides whether or not to take any action to adapt to the climate shock. The adaptation decision at this initial step for each type of shock can be solved by standard probit regression estimating the relationship between a latent discrete binary decision dependent variable y_i (adapt: $A_i = 1$; not adapt $A_i = 0$) and a set of explanatory variables (x_{ij}) and error term μ

$$y_i = x_i\beta_i + \mu_i \quad \text{……(1)}$$

$$yi\begin{cases} A = 1 \ \ if\ y_i > 0 \\ A = 0 \ \ otherwise \end{cases}$$

In the second step, after the decision to adapt an adapting household will select a particular adaptation strategy from among the available options that may be used simultaneously as complements or substitutes. For this purpose, the standard binary (univariate) probit model in the first Step was expanded to multivariate probit regression (MVP) with a standard normal distribution to assess factors influencing the selection of various adaptation strategies. The MVP was specified as:

$$y_{i2} = \begin{cases} A = 1 \ \ if\ y_{i2} > 0 \\ A = 0 \ \ if\ y_{i2} < 0 \end{cases}$$
$$; \quad \text{……(2)}$$
$$y_{i5} = \begin{cases} A = 1 \ \ if\ y_{i5} > 0 \\ A = 0 \ \ if\ y_{i5} < 0 \end{cases}$$

Where: i_1=inorganic fertilizer, i_2=improved seeds, i_3= legume intercropping, i_4=soil and water Conservation and i_5= animal manure. The multivariate probit model was specified as

$$y_{ij} = \beta_0 + \beta_1 x_1 + \text{.........} + \beta_{10} D_i + \varepsilon_i \quad \text{……(3)}$$

Where x_i = independent variables defined as follows: x_1 is farm plot size, x_2 is distance from the farm plot, x_3 is education of household, x_4 is experience, $x_5$is distance to the input market, x_6 is extension service, x_7 is Household asset index, x_8 is coefficient of rainfall variation, x_9 is rainfall satisfaction index, x_9 is access to government subsidy. β_0 is constant, $\beta_1 - \beta_{10}$ are regression coefficients, and e is error term. The error terms in equation (3) jointly follow a multivariate normal (MVN) distribution, with zero conditional mean and variance normalized to unity. 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 farm technology. This assumption means that equation (3) gives a MVP model that jointly represents decisions to adopt a particular farming practice. 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 technologies.

3.3 Data Collection

The sampling frame for the study included all smallholder farmers in Pangani basin which was about 747,641 (URT, 2012). Using Yamane (1973) the sample size was calculated to approximately 420. A multistage sampling technique was used to select the farmers. The first stage involved selection of agricultural /ecological zones based on the rainfall pattern. These classifications of high, Moderate and low rainfall were meant to obtain the actual range of adaptation measures which have been adopted by farmers under different rainfall patterns. The second stage involved selection of the districts from each zone (Table 1). The selection of villages constituted the third stage; two villages were chosen from each of the selected district making a total of 12 villages in the sample. The villages were purposefully selected with the assistance of staff from District Agricultural Information and Cooperative Officers (DAICO) within Pangani basin as well as staff from Pangani Basin Water Board Authority (PBWA). The last stage involved the selection of farmers from the selected villages. In each village, 35 households were randomly from the village household register giving a total of 420 respondents.

Table 1. Distribution of Sample Villages

Region	District	Name of village	Rainfall category	Number of respondents		
				Male	Female	Total
Arusha	Arumeru	Samaria	Low	29	6	35
		Mareu	High	27	8	35
Kilimanjaro	Hai	Kimashuku	High	28	7	35
		Mijongweni	Low	30	5	35
	Moshi Rural	Sambarai	High	28	7	35
		Ghona	Moderate	26	9	35
	Same	Njoro	Low	27	8	35
		Mabilioni	Low	30	5	35
Tanga	Korogwe	Mafuleta	Moderate	31	4	35
		Kwagunda	Moderate	27	8	35
	Pangani	Boza	Moderate	32	3	35
		Kigurusimba	Moderate	30	5	35

A structured questionnaire was employed to collect information from the smallholder farmers. The questionnaire contained a wide range of information from the household's understanding of climate change, households' production activities and plot specific characteristics, including adoption of sustainable agricultural practices for each household. Other information collected at the plot level was tenure status of plots, crops grown, crop production estimates, labor inputs associated with each type of agricultural activity, fertilizer usage, and seed types. Key socioeconomic elements collected about the household include age, gender, education level, family size, asset ownerships, participation in extension and training services, membership in farmers' organizations, and distance from the household to the input and output markets and availability of extension officers. Rainfall data were analyzed using Instat statistical package while the remaining data were analyzed using Excel and STATA statistical packages.

4.0 Results

4.1 Descriptive Statistics

Table 2 shows descriptive statistics for the variables that we use to explain technology adoption in Pangani River Basin. As explained in the previous section, farmers may adopt certain technologies on some of their plots but not on others. Therefore the analysis was carried out at the plot level, with farm and household level variables referring to the farms and households that operate the respective plots. The mean values of variables which were used to explain variation in technology adoption among farmers are shown in Table 2. Plot level specific attributes included plot: altitude, size, soil fertility, slope, tenure status and the distance from the plot to the farmer's home (walking distance in minutes). Accordingly, the descriptive statistics show that on average, landowners operate on 1.65 plots each, and these plots were spatially adjacent (as far as 15 minute walking time away on average). The variable distance to the plot is an important determinant of the technology adoption because of increased transaction costs on the farthest plot, particularly the cost of transporting bulky materials/inputs (Teklewold *et al.,* 2013).

Table 2. Descriptive summary of selected variables

Variable name	Mean	Std dev	Minimum	Maximum
Plot size (in acres)	1.651	1.607	0.25	6.0
Total number of maize farm plots	1.51	0.70	1.00	4.00
Distance to the farm plot in walking minutes	9.517	2.889	5	25
Age of household head (years)	47.53	10.35	82	31
Household head highest level of education (years)	7.67	2.280	0	18
Household size in adult equivalent	4.12	1.230	1.6	8.56
Experience in maize farming (years)	18.74	8.96	5	48
Coefficient of variation of rainfall (1983-2013)	0.23	0.05	0.14	0.36
Number of maize plots observation =682				
Number of household observation=420				

Household characteristics included household head´s education level, age, and experience in maize farming. Other variables were family size measured in adult equivalent, and household asset. The wealth index was computed based on ownership of durable goods and the condition of the house. This index was used as a proxy for Household capital. The assumption was that that households that own more capital are wealthier and more likely to take risks associated with the adoption of new technologies. Institutional factors considered in this study included distance to the factor market measured in kilometers, access to extension services and membership to financial organization. Distance to the factor market and poor access to transportation services can negatively influence the smallholder's decision to adopt some technology if they have to travel and incur significant transport costs. Further Pertaining to climatic variables, the historical data on rainfall patterns mean rainfall and the coefficient of variation (CV), for the respective periods: 1983-2013 was used to capture farmer expectations about climate at the beginning of the season when they make decisions on use of inputs. The rainfall subjective index of farmer's perception of rainfall trend and occurrence was 0.33 which indicates that during the growing season the rainfall situation was not desirable. In this study farm technologies considered included inorganic fertilizer, improved maize seed varieties, maize-legume intercropping, SWC and use of manure that are considered to help reduce exposure to climate shocks and at the same time also help as adaptation strategies. Table 2 presents the proportion of households that implemented the aforementioned agricultural practices on their plots disaggregated by rainfall pattern.

Use of improved maize seeds including hybrids and Open Pollinated Varieties (OPVs) seeds. The plot planted with improved maize varieties is about 53.8%. Looking across the different rainfall pattern, there seems to be no significant differences in the use of inorganic fertilizers. Mineral fertilizers were adopted on 42.2%. Maize legume intercropping was practiced on about 37.10% of the plots during the cropping season. This technology can help increase crop productivity through nitrogen fixation and therefore contributes to maintain productivity in a changing climate. Soil and Water Conservation (SWC) investment existed on nearly 37.98% of the total plots of sampled households. The dominant SWC practices considered in this study were; terracing, live plants or tree belts/barriers, and contour bunds built either earth or stones. The SWC structures provide multiple on-farm benefits such as increased and more stable yields by reducing water erosion, improving water quality, and promoting the formation of natural terraces over time (Asfaw *et al.,* 2014). However animal manure was used on about 18.07% of the sample maize plots.

Table 3. Descriptive summary of adoption of adaptation practices

	High rainfall (N=181)		Moderate rainfall (N=295)		Low rainfall (N=203)		Total (N=682)		Sig diff
	Frequency	%	Frequency	%	Frequency	%	Frequency	%	
Inorganic fertilizer	112	62.43	101	33.56	79	38.92	292	42.82	11.04***
Improved maize seeds	132	72.93	121	40.60	114	56.16	367	53.81	6.145**
Legume Intercropping	105	58.01	88	29.53	60	29.56	253	37.10	23.73***
Soil water conservation	68	37.57	109	36.58	82	40.39	259	37.98	2.643
Manure	31	17.12	49	16.61	47	23.15	127	18.07	3.001

4.2 Regression Analysis

Table 4 presents the results of the Multivariate Probit (MVP) adoption model. The p-value of the Wald test statistic for the overall significance of the model was highly significant (P=0.000) indicating that the multivariate probit regression model adequately fits the data well. The likelihood ratio test "rho" was highly significant ($p<0.000$) implying that the covariance of the error terms across equations are not correlated thus justifying the use of the MVP over single-equation probit models. This is supported by the correlation between error terms of the adoption equations reported in table (4). The estimated correlation coefficients were statistically significant and different from zero in seven of the ten pair cases, where one coefficient was negative and the remaining six, were positive suggesting that farmers technology adoption equations are not independent of each other, and hence a multivariate probit approach is appropriate in this case. Furthermore, the positive and significant correlation coefficients of the error terms indicate that there is complementarity (positive correlation) between different farm technologies being used by farmers, which supports the assumption of interdependence between the different technology options. From table (5), the use of inorganic fertilizer was complementary to the use of improved seed but substitutable with manure. The positive correlation coefficient between inorganic fertilizer and improved seed was the highest among all (26.4%) implying that productivity potential of high yielding varieties is highly dependent on a farmer using inorganic fertilizer. The cross-technology correlation may have an important policy implication in that a policy change that affects one farm technology can have spillover effects to other farm technologies.

The MVP results reported in Table 5 show that the adoption decisions of different farm technologies are quite distinct and to a larger extent the factors governing the adoption decision of each of them are also different suggesting the heterogeneity in adoption of farm technologies. The MVP coefficient estimates show the importance of climatic variables that is coefficient of rainfall variation in explaining the probability of farm households' decision to adopt different agricultural practices. According to this results, greater variability in rainfall captured by the coefficient of rainfall variation increased the probability of a farmer using improved seeds and adopting SWC measures. Closely related to this was the value of Rainfall satisfaction index which was positively associated with adoption of inorganic fertilizer and SWC practices. That means, the probability of a farmer adopting inorganic fertilizer and SWC practices was high in areas where rainfall was more reliable in terms of timing, amount and distribution. These findings suggest that farmers are responding to climate patterns, as represented by their adaptation strategies. Hence information on climate variability should be an integral part of extension activities.

Table 4. Covariance matrix of the regression equations between adopted farm technologies using the MVP joint estimation model

	Inorganic fertilizer	Improved seeds	Legume intercropping	Soil-water conservation
Improved seeds	0.264**			
Legume intercropping	0.198**	0.152**		
Soil-water conservation	0.026*	0.088*	0.043	
Manure	-0.168**	0.065	0.124**	0.035
Adjusted LR χ^2 (10) =65.47				
Prob > χ^2 = 0.0000				

*,** and *** indicate statistical significance at 10, 5 and 1% respectively

Wealth measured by the value of durable household assets had positive influence on the adoption of inorganic fertilizer, improved seeds and intercropping. This is probably because wealthier farmers may have the capacity to purchase external inputs and may be more able to take risks. Plot distance to the input market had a significant negative effect on the adoption of inorganic fertilizer which reflects the difficulty of remote households to assess and adopt new technologies indicating that distance to major markets constitutes a time Constraint on the ability of farmers to access information and inputs. Similarly plot distance to residence, have a negative impact on application of soil water conservation and use of animal manure.

Better access, apart from influencing availability of technology, can influence the use of output and input markets, and the availability of information and support organizations as well as the opportunity costs of labor (Wollni *et al.,* 2010). The fertility level of the plots also influences the type of technology practiced; good soil fertility positively influences adoption of improved seed varieties and inorganic fertilizer. Use of improved seed and inorganic fertilizer is a high investment technology thus farmers are more likely practice it in more fertile plots so as to ensure maximum returns on their investment. Similar to these findings, Kassie *et al.,* (2010) also found that farmers farming on a fertile plots are more likely to use improved seeds and inorganic fertilizer compared to farming in less fertile plots.

Table 5. Multivariate Probit Results

	Inorganic fertilizer	Improved seeds	Legume intercropping	SWC	Manure
Variables	Coeff	Coeff	Coeff	Coeff	Coeff
Plot size (in acres)	0.048	-0.084	0.436	0.32	-0.441
Distance to the farm plot in walking minutes	-0.155	0.198	-0.105	0.317*	-1.393***
Irrigation use (=1 if yes)	0.55*	-0.06	-0.28	0.08	0.19
Household head education (years)	0.004	0.015	0.023	-0.062*	-0.003
Household size in adult equivalent	0.53	1.456*	-0.5915*	-1.141	0.076
Experience in maize farming (years)	-0.027	-0.145	0.081*	0.128	0.043
Distance to the input market (km)	-0.03	-0.027	0.018	-0.060*	0.129
Access to extension services (=1 if yes)	0.744**	0.376	-0.088	0.469*	0.316
Access of government subsidy in 2013 (=1 if yes)	0.756***	0.668***	-0.025	0.096	-0.107
Household asset index	0.19*	0.49**	0.14*	-0.06	-0.03
Coefficient of variation of rainfall (1983-2013)	-2.17	1.92*	-0.78	2.23*	-1.27
Rainfall satisfaction index	0.04*	-0.11	-0.26	0.32*	-0.28
Constant	-0.59	-6.07***	-5.395**	2.474**	-1.208
Log-Likelihood=-335.643					
LR test of rho chi^2 (10) =26.349					
Wald chi^2=0.0033					
Number of observations (plot) 682					

*,** and *** indicate statistical significance at 10, 5 and 1% respectively

5.0 Conclusion and Policy Implication

Research and adoption of technologies are crucial in increasing agricultural productivity and lowering the poverty levels in developing countries. However, there are some disagreements about which type of technologies are most appropriate for the developing countries. In reality there is no single approach that will work in each situation and the suitability of these technologies varies with different conditions. This study seeks to determine conditions under which each of these technologies are adopted using data collected from all the maize growing areas in Pangani river basin in Tanzania with the focus being on small holder farmers. In addition, the paper seeks to find out what the combination of technologies farmers mostly adopt. The study establish that there is an interdependence between farm technologies that are adopted by farmers for climate change adaptation implying that the adoption decision of a specific technology is correlated with the adoption of another technology. Findings further suggest that different conditions ranging from plot level attributed to rainfall variation influence the type of technology adopted by the farmers. Therefore, these factors should be considered when planning, implementing and evaluating extension programs for dissemination of each of these technologies.

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