Farm Technologies and Production Risk in the Face of Climate Change in Tanzania

A. Moshi[1*]*, J. Hella*[2] *and A. Isinika*[3]
[1]*PhD Candidate at Department of Agricultural Economics and Agribusiness, Sokoine University of Agriculture*
[2]*Department of Agriculture Economics and Agribusiness, Sokoine University of Agriculture*
[3]*Institute of Continuing Education, Sokoine University of Agriculture*
**Corresponding author: abmoshi@yahoo.com*

***Abstract**: In countries where insurance and credit markets are thin or missing, production and consumption risks play a critical role in the choice and use of production inputs and adoption of new farm technologies. This paper investigated the effect of selected farm technologies and their risk implications in different rainfall patterns of Pangani river basin in Tanzania. Given the production risks posed by climate change, such information can be used by decision makers to identify appropriate agricultural practices that act as a buffer against climate change. Using a household and plot-level data set, Just and Pope framework was applied to using a quadratic production function to investigate the impact of selected farm technologies on average crop yields and the variance of crop yields, while controlling for several household and plot level factors. The results revealed that farm technologies perform differently in different rainfall areas, which underscores the importance of careful geographical targeting when promoting and up-scaling farm technologies adoption to climate change.*

Key words: Climate change, risk, farm technologies

INTRODUCTION

Climate change is a serious threat for agriculture, food security and the fight against poverty in the world. 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 (Agrawal *et al.,* 2003; IPCC, 2013). Frequent droughts represent the most pressing constraints to farmers the direct effects being reduced productivity and reduced area under cultivation, each of which contribute to reduced overall crop production (Bezabih *et al.,* 2010). Such reduction has forced many families to deplete their assets to support household consumption with long-term consequences (Dercon and Christiansen, 2007; Westengen and Brysting, 2014).

Pangani river basin, situated in the north-east part of Tanzania, is a typical example where smallholder farmers are facing a wide range of uncertainty in their farming. The basin has been projected to face declining rainfall and drought due to climate change (Ndomba, 2010). The temperature in Pangani basin is predicted to rise by 1.8^{o}C and 3.6^{o}C by 2050 and 2100 respectively (IUCN, 2009). These changes are already having an adverse impact on agricultural and natural resource production systems and hence livelihoods in this area. Rainfall variability and associated drought have been major causes of food shortage and famine in the basin (URT, 2014). During the last ten years, the basin has experienced many severe droughts leading to production levels that fell short of basic subsistence levels for many farm households (IUCN, 2003; Ndomba, 2010). Harvest failure due to weather events is the most important cause of risk-related hardship of rural households, with adverse effects on farm household consumption and welfare (Dercon, 2004, 2005). More erratic and scarce rainfall and higher temperature imply that farmers will be facing a larger periods of uncertainty.

To mitigate the decreasing farm productivity resulting from climate change effects, some farmers have kept up with their traditional farming practices which are no longer suitable taking into account the unpredictability of rainfall patterns across the country. On the other hand the government of Tanzania and other development partners have had various initiatives to enhance agricultural productivity, especially among smallholder farmers. In their programmes improved seeds of different crop varieties have been introduced and disseminated, fertilizer prices have been subsidized, and soil and water conservation (SWC) technologies have been promoted (Salami *et al.,* 2010; Asfaw *et al.,* 2013). Despite these efforts, adoption rates for majority of the improved farm technologies remains low and varying across households and regions (Lyimo *et al.,* 2014). Moreover, even for technologies that have been better adopted like inorganic fertilizers and improved maize seeds adoption rate are still low i.e.12 percent and 20 percent of the smallholder farmers respectively (URT, 2014). Further report shows that yield have either been declining or stagnating contrary to common belief that these technologies are yield-enhancing (Kangalawe and Lyimo, 2013). This leads us to pose the following questions: Is climate change adaptation a successful risk management strategy that makes the adapters' more resilient to current environmental risk? The answer to this question requires one to look at the risk implications of adaptation to climate change in the area. This is because some inputs may reduce the level of output risk, whereas others may increase it (Shankar *et al.,* 2008).

That being the case, it has been noted that in the adoption of technologies, farmers consider not only impacts on crop yields but also risk effects (Kassie *et al.,* 2010). This is because in most agricultural production processes, we can observe random production shocks only after input decisions have been made. This is in contrast to the standard case where certainty is presumed, where the only determinants of optimal input demands are the structure of the production technology as well as input and output prices facing the producer. In the presence of risk, the producer's risk preference structure and expectation formations are also important in determining optimum behavior. Although it is expected that all inputs contribute to increase output, some inputs may reduce the level of output risk, whereas others may increase it (Guttormsen and Roll, 2013). This situation affect the uptake of farm technologies. This paper, focus on analyzing the risk implications of various improved farm technologies for crop production in Tanzania using the parametric stochastic production function framework of Just and Pope (1978).

The analysis identified the risk-increasing and risk-reducing effects of different improved farm technologies on crop production in different rainfall pattern of Pangani river basin in order to isolate which technologies are best suited to particular regions and agro-ecological niches. These farm technologies include maize-legume intercropping, soil and water conservation (SWC) practices, organic fertilizer, inorganic fertilizer and high yielding maize varieties. Empirical evidence regarding the effect of these technologies will help improve geographical targeting of improved farm technologies by policymakers, and development agencies as part of an effort to promote adaptation to climate change at the farm level.

THEORETICAL FRAMEWORK

In analyzing risks involved in farm production operations, considerable research has attempted to provide empirical evidence on how risk influences the nature of decisions in agricultural production. These attempts can be categorized into two groups of studies. The first group has aimed at estimating producer’s attitude towards risk that influence input allocation and output supply decisions. These studies have employed either the experimental or econometric approaches to elicit risk attitudes of individual producers. The experimental approach is based on hypothetical questionnaires regarding risky alternatives or risky games with or without real payments (Wik *et al.,* 2004). For example, Binswanger (1981) used risky games with real payments to measure peasant's risk preferences in an experiment in India. The econometric approach is based on individuals' actual behaviour assuming expected utility maximization. Studies that have used this approach to elicit producer's risk attitudes include; Antle (1983), Pope and Just (1991).

The second group of studies have attempted to investigate the influence of risk on agriculture production by directly incorporating a measure of risk in the traditional production functions. Such studies include work by Just and Pope (1979) who focused on production risk, measured by the variance of output, and suggested use of production function specifications satisfying some desirable properties. The main focus in their specification is to allow inputs to be either risk increasing or risk decreasing. A number of empirical studies such as Farnsworth and Moffitt (1981), Smale *et al.* (1998), Fufa and Hassan (2003) and Di Falco *et al.* (2007) have used the Just and Pope stochastic production function to determine the effect of inputs and levels of input use as well as technology on output distribution. Farnsworth and Moffitt (1981) used the risk flexible Just and Pope Production model to examine cotton production under risk in California. In this study, the Just and Pope stochastic production function was used to analyze the effect of improved farm technologies on the distribution of maize yields in Pangani river basin, Tanzania. The J-P stochastic production function is represented as:

$$y = g(x, v) \quad \text{(i)}$$

> Where: y is output, x is a vector of controllable inputs (e.g. fertilizer, land, labour), v is vector of non-controllable inputs (e.g., weather conditions), and $g(x, v)$ denotes the largest feasible output given x and v.

Of particular interest, here are the interactions between the inputs (x, which include maize seeds and inorganic fertilizer) and the random variables (v, which represent production uncertainty).

The focus on production uncertainty as represented by the stochastic production function $y = g(x, v)$, where weather conditions (v) are not known at planting time, but the farmer has a subjective distribution regarding the weather variable. Just and Pope (1978) proposed to specify the production function as follows:

$$g(x,v) = f(x) + [h(x)]^{1/2} e(v) \quad \text{(ii)}$$

Where $f(.)$ = mean production function,

$h(.)$ = variance (or risk) function,

x and z = vectors of inputs,

e = the exogenous stochastic disturbance or production shock (error term)

$g(x,v)$ = as previously defined

$h(x) > 0$ and $e(v)$ = random variable with mean zero and variance 1

The expected value of output is given by equation (iii) as:

E (y) = f(x) ....(iii)

While the variance of *y* is a product of the variance of (e) and *(h(x)* which is equal to *(hx)*. It is presented as:

$E(y) = f(x)$ and $Var(y) = Var(e)h(x) = h(x)$. This makes $\frac{\delta Var(y)}{\delta x} = \frac{\delta h}{\delta x}$ (iv)

Then it follows that when $\frac{\delta h}{\delta x} > 0$, then the corresponding inputs (x) is risk-increasing implying that, a rise in that variable indicates an increase of the variability of yield. On the other hand if the derivative of the variance of output is negative ($\frac{\delta h}{\delta x} < 0$) then the input is risk-decreasing that is it indicates decrease of the variability production. Note that $e(v)[h(x)]$ behaves like an error term with mean zero and variance equal to $h(x)$. From an econometric viewpoint, this formulation is also useful because the variance function can be interpreted as a heteroskedastic disturbance term. This can be seen by reformulating the Just and Pope function in equation (ii) as $y = f(x;\alpha) + \mu$.

Where *u* is the error term with variance $\text{var}(\mu) = [h(x;\beta)]^2 \sigma_\varepsilon^2$

EMPIRICAL SPECIFICATIONS

In estimating the J-P function, three functional forms are used to estimate the production functions: Cobb-Douglas, quadratic and translog functions have been used for the Just and Pope Production function (Kim and Coelli, 2009). Because of the multiplicative interaction between the mean and variance, a translog functional form would violate the Just and Pope assumption (Kumbhakar, 1993) and for Cobb-Douglas production function provided poor estimate. The linear quadratic function has been the best functional form in different studies (Kebede and Adenew, 2011; Khanal *et al.,* 2010), for two reasons. Firstly, it is consistent with JP postulates that there is an additive interaction between the mean and variance output function. Secondly, it is flexible in the sense of a second-order approximation of any unknown mean output function (Kumbhakar *et al.,* 2011). In the present analysis, linear quadratic functional form was used to estimate the production and variance function this production function was used to specify farm practices used by the farmers namely: inorganic fertilizer, improved maize seeds and legume intercropping, animal manure and soil water conservation. Due to diversity in topography, and the possibility of differences in weather, rainfall and altitude were included in the model to assess their importance in influencing maize yield and variability. The mean output function (f) for the representative farm is expressed as follows:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_1^2 + \beta_3 x_2 + \beta_4 x_2^2 + \beta_5 x_3 + \beta_6 x_3^2 + \beta_7 x_4 + \beta_8 x_4^2 + \beta_9 x_5 + \beta_{10} x_6 + \beta_{11} x_1 x_2 + \varepsilon_i \qquad (vi)$$

Where: y_i = Maize yields in Kilograms per hectare (kg/ha).

x_1 = Amount of fertilizer used per hectare (Kg/ha),

x_2 = amount of improved maize seeds in kilogramme per hectare,

x_3 = Amount of manure applied in kilograms per hectare (kg/ha),

x_4 = Rainfall precipitation in millimeters during planting season,

x_5 = Dummy variable for legumes intercropping,

x_6 = Dummy variable for soil water conservation,

x_7 = altitude (proxy for temperature), the variance function was specified as:

$$e^2 = \beta_0 + \beta_1 x_1 + \beta_2 x_1^2 + \beta_3 x_2 + \beta_4 x_2^2 + \beta_5 x_3 + \beta_6 x_3^2 + \beta_7 x_4 + \beta_8 x_4^2 + \beta_9 x_5 + \beta_{10} x_6 + \beta_{11} x_1 x_2 + \varepsilon_i \qquad (vii)$$

Where: e^2 = variance of maize yield

All other variables are as previously defined.

STUDY AREA AND DATA

The data used in this study were collected from the farmers household survey conducted between November 2013 and February 2014 in Pangani river basin. The sampling frame for the study included all smallholder farmers in Pangani basin which, during the last census in 2012 was about 747,641 (URT, 2012). From the sampling frame, a representative sample size of 420 smallholder farmers with known confidence and risk levels was selected based on the work of Yamane (1967). The sample of small holder farmers were obtained using a multistage sampling technique. Sample selection for the study sites was meant to identify and accommodate a wide range of adaptation measures which have been adopted by farmers under different rainfall patterns. The first stage involved selecting agricultural/ecological zones based on the rainfall pattern. Based on the classification of rainfall as: high, moderate and low rainfall. The second and third stages involved selection of districts from each zone followed by villages (Table 1).

Two villages were chosen from each of the selected districts making a total of 12 villages in the sample. The villages were purposefully selected with the assistance of staff from the District Agricultural Information and Cooperative Officers (DAICO) for each district within Pangani basin as well as staff from Pangani Basin Water Board Authority (PBWA). The last stage involved selection of farmers. From each village in the sample 35 households were randomly selected from the village register of household heads; a total of 420 respondents were identified, and considered to have met the conditions for participation in the study. Data were collected from farmers using a structured questionnaire and face-to-face interviews. The questionnaire solicited information on household profile, agricultural productivity, understanding of climate change, climate change adaptation and coping strategies on household profile, agricultural productivity, understanding of climate change, climate change adaptation and coping strategies.

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
Total				**345**	**75**	**420**
Percentage				**82.14**	**17.86**	**100**

Data Analysis

The data were compiled, summarized and analyzed using Excel software for data management at initial stages. Stata software was used for descriptive statistics, and regression analysis. Descriptive statistics that were used to analyses the data included percentages and frequencies. Regression analysis involved estimation of the mean and variance of maize yield. There are two estimators that provide consistent estimates of the parameters of the production function and the variance function; the three-stage feasible generalized least squares (FGLS) and the maximum likelihood (ML). The FGLS estimator has often been used in empirical studies of production risk (Di Falco *et al.,* 2007; Kato *et al.,* 2009). However, the ML estimator provide asymptotically more efficient estimates of the variance function parameters than FGLS (Harvey, 1976). Hence it was used in this study.

The first step when analyzing production risk using the Just and Pope function is to assess whether there is significant marginal output risk in input levels. Given that production risk is specified as being heteroskedastic in the J-P framework, any test for the presence of heteroskedasticity can be used. A failure to detect heteroskedasticity is regarded as evidence that production risk does not exist, and the analysis should follow conventional deterministic framework approach. If production risk is detected, there are two issues of interest in the analysis: the mean production function and the variance function.

In the second step we predicted the residuals and then constructed squared residuals. The squared residual were then used as the dependent variable for the variance function estimation *h(x)* using a maximum likelihood estimator. The main interest is on these third-stage estimates of the variance function, where a positive coefficient implies risk-increasing effects, and conversely a negative coefficient implies a risk-decreasing effect of the input on crop output.

The analysis was implemented at the plot level because the focus of the study is on farm technologies that were observed at the plot level. Data for the dependent variable was also measured at the same level. This level of analysis is advantageous because it captures more spatial heterogeneity and also helps to control for plot-level covariates that condition crop production and hence help to minimize the omitted variable bias that would confound household-level analysis. For the full-sample estimations, village fixed effects were included to control for unobserved time-invariant characteristics that might be correlated with the dependent variable, which also mitigates for the problem of omitted variable bias. The results were presented in the forms of tables and graphs.

RESULTS AND DISCUSSION

Descriptive Results

Findings from the survey revealed that the smallholder farmers in the study area used a mix of farm technologies to manage and reduce the sources of risk resulting from climate change. Responses on the main on-farm technology practices that are adopted in response to rainfall variations are presented in Table 2. The responses include the use of improved maize seed varieties, application of manure, application of inorganic fertilizer and soil and water conservation.

Table 2: Percentage distribution of respondents using selected farm technologies by rainfall pattern

Farm technologies	High rainfall (N = 181)	Moderate rainfall (N = 295)	Low rainfall (N = 203)	Total Sample (N = 682)
Inorganic fertilizer	62.43	33.56	38.92	42.82
Improved maize seeds	72.93	40.60	56.16	53.81
Legume Intercropping	58.01	29.53	29.56	37.10
Soil water conservation	37.57	36.58	40.39	37.98
Manure	17.12	16.61	23.15	18.07

The study revealed that, about 53.8% of the sampled households used improved maize variety during the 2013/14 cropping season. Further across the three rainfall patterns, higher adoption rate of improved maize varieties occurred in high rainfall areas (72.9%) compared to only 56.16% in low rainfall areas and 40.6% in moderate rainfall areas. The higher adoption rate in low rainfall areas compared to moderate rainfall areas should be a reflection of adaptation to climate change.

This differences imply that, the diffusion of improved maize seed varieties had strong regional biases across the three rainfall zones. Hence, promoting the use of improved maize varieties is important in some of the rainfall patterns more than in others. The result further attest that very often farmers cultivate more than one kind of maize variety as the distribution of maize varieties to hedge against rainfall shortfall. Results from focused group discussion revealed that farmers switch from one maize variety to the other variety between years depending on the expectation of rainfall. One of the reasons for switching was availability of government subsidy and income, training from extension agents and weather information.

Further, the findings show that, about 37.1% of the surveyed farm plots practiced intercropping of maize with legumes. Leguminous plants have a special relationship with nitrogen-fixing bacteria called Rhizobium. By biologically fixing nitrogen levels in the soil, legumes provide a relatively low-cost method of replacing nitrogen in the soil, enhancing soil fertility and boosting subsequent crop yields (Winterbottom *et al*., 2013). This practice was found higher in high rainfall areas (58.1%) compared to (29.53%) and (29.56%) in moderate and lower rainfall areas respectively.

Pertaining to soil fertility management, mineral fertilizers were adopted on 42.2% of the farm plots. A higher proportion of farm plots (62.43%) in high rainfall areas used inorganic fertilizer compared to only 38.92% in low rainfall areas and moderate rainfall areas 33.56%. Low application ofinorganic fertilizer in Sub-Saharan Africa has been pointed as one of the major constraints to achieving a Green Revolution (IFDC, 2006).

Majority of farmers do not use fertilizer due to the notion that their plot was fertile enough for maize production. Some farmers lack funds to buy fertilizer. Use of manure, is another important component of a sustainable agricultural system, which also captures economies of scope in crop-livestock systems. It is a major component of a sustainable agricultural system with the potential to sustain long-term maintenance of soil fertility and supply of nutrients, especially nitrogen and phosphorus (Salami *et al.,* 2010).

Soil and Water Conservation (SWC) structures provide multiple on-farm benefits such as to avoid soil erosion and acidification (Kassie *et al.,* 2008). In this study SWC practices were used on about 37.98% of the total plots in the sample being higher in low rainfall areas (40.39%) followed by high rainfall areas (37.57%) and lowest was the moderate rainfall areas. The most dominant SWC practices were; terracing adopted on (11.5%) of the farm plots followed by live plants or tree belts/barriers (14.6) and contour bunds built using either earth or stones (11.88%).

Econometric Results

Prior to estimating the mean and variance functions, three diagnostic tests were taken to ensure valid results including test for multicollinearity, endogeneity and heteroscedasticity. The test for multicollinearity problems reveals that, the VIFs were less than 2.0 and the pairwise correlations were also less than 0.5, indicating that the standard errors were not affected by collinearity problems and therefore multicollinearity was not a problem. Concerning presence of endogeneity, Wu-Hausman test was performed to determine whether variables were endogenous to the model. The null hypothesis that the variables were exogenous was not rejected since the P-value was very high (0.61) indicating absence of endogeneity within the variables to be estimated.

Results from the mean function are reported in Table 3. The results showed that, for inorganic fertilizer the coefficient of the linear term is positive, but the interaction effect of inorganic fertilizer and improved maize seeds is negative in both high and moderate rainfall areas. However, when, evaluated at the sample means, the elasticity of mean maize yields with respect to inorganic fertilizer was 0.145, which indicates that inorganic fertilizer has a positive effect on increasing maize productivity. This could be attributed to the low nutrient composition of the soil that cannot meet crop nutrient demand in the Pangani basin (Kaihura *et al*., 2001).

Furthermore, the estimated coefficient for the use of improved seeds is positive but only statistically significant in high rainfall areas. However, the interactive effects of inorganic fertilizer and improved maize seeds represented by the coefficient of the interaction term was statistically significant in all three rainfall patterns with evidence of increasing marginal returns. This means there is good complementarity between the two inputs towards increasing maize productivity.

Table 3: Parameter estimates for the mean yield function

Parameter	Coefficient for the Mean production function			
	High rainfall	Moderate rainfall	Low rainfall	Overall
Inorganic fertilizer	1.01***	2.46**	4.03**	1.39***
Inorganic fertilizer squared	-0.01*	-0.03**	-0.01	0.01*
Improved seeds	0.57*	0.31	0.09	0.56
Inorganic fertilizer×Improved seeds	0.06***	0.01	0.02	0.05***
Manure	-0.05	-0.18	-0.30	-0.20
Manure squared	0.001	0.002	0.003	0.002
Precipitation	0.13	0.21*	0.11	0.20
Precipitation squared	0.00	-0.01	-0.10	0.03
Legumes intercropping	0.23*	0.69**	0.33	0.74**
Soil water conservation	0.43*	1.63	0.15**	0.88***
Altitude	0.08	-0.06	0.01	-0.07*
Constant	3.256***	6.147***	5.614	4.574***
Adj R-squared	0.773	0.6981	0.7926	0.7563

Significance levels are denoted by one asterisk (*) at the 10 percent level, two asterisks (**) at the 5 percent level, three asterisks (***) at the 1 percent level.

The results also revealed that, rainfall precipitation had a significant positive effect on maize yield in moderate rainfall areas only. When evaluated, the elasticity of maize yields with respect to rainfall precipitation was positive (0.178) implying that a 1 percent change in rainfall precipitation will change maize yield by 0.178 percent. Soil and water conservation showed significant positive impact in high and low rainfall areas.

For the variance function, parameter estimates are shown in Table 4. Both the linear and quadratic coefficients of inorganic fertilizer were statistically significant in higher and moderate rainfall areas. The positive linear term and negative quadratic term imply that inorganic fertilizer reduces the variance of yields. When evaluated for the other variables, inorganic fertilizer decreased the yield variance by 0.124. The coefficient of the interaction effect between inorganic fertilizer and improved maize seeds was negative and statistically significant. This implies that the range of values where improved maize seeds reduces risk exposure tends to increase with use of inorganic fertilizer, reflecting the synergy effects of inorganic fertilizer on improved seeds towards reducing crop failure under the harsh environmental conditions. However, in low rainfall areas fertilizer use was associated with a positive and significant effect on the variability of maize yield implying that inorganic fertilizer increase yield variability in this area. This phenomena of increasing yield variability in low rainfall areas that is associated with fertilizer use, could be attributed to variation in application levels (rate) and management (timing and application methods) among farmers and also due to lower water potential in some areas, which limits fertilizer uptake by plants (Thierfelder and Wall, 2012). This is also consistent with Fufa and Hassan (2003) who argued that the yield response of crops to different levels of fertilizer under farmer's management conditions depend on a number of interacting factors that include bio-physical factors such as soil type, the time and amount of rainfall, date of planting and management practices such as the rate and method of fertilizer application.

Table 4: Parameter Estimates for variance function

Parameter	**Coefficients for Variance function**			
	High rainfall	**Moderate rainfall**	**Low rainfall**	**Overal l**
Inorganic fertilizer	-0.058*	-0.012	0.0132*	-0.004*
Inorganic fertilizer squared	-0.002*	0.002	-0.001*	0.002
Improved seeds	-0.004	-0.005	0.003	-0.003
Inorganic fertilizer× Improved seeds	-0.001*	-0.002*	0.001	0.003*
Manure	0.003	0.001	0.007	0.009
Precipitation	-0.024	0.011	-0.919*	- 0.0003*
Precipitation squared	0.003	0.002	0.004*	0.002
Legumes intercropping	0.188	0.384*	0.015	0.116
Soil water conservation	0.211	0.200	-0.666*	-0.182
Altitude	0.007	0.002	0.002	0.001
Constant	0.584	-1.466	0.284	0.593
Adj R-squared	0.093	0.110	0.103	0.091
Log-likelihood function 204.96				

Significance levels are denoted by one asterisk (*) at the 10 percent level, two asterisks (**) at the 5 percent level, three asterisks (***) at the 1 percent level.

The coefficient of the interaction term for improved seeds and inorganic fertilizer is negative and statistically significant from zero in high and low rainfall areas. Since the coefficient of improved seed was negative but not statistically significant in high and low rainfall areas, a negative and significant interaction term implies that the range of values where improved seed reduce risk exposure tends to increase with increasing use of inorganic fertilizer. The results further showed that rainfall had a negative and significant effect on the variance of maize yield implying that when the amount of rainfall increases maize yield stability improves and hence reducing the risk that farmers in that area face. In low rainfall areas, the coefficient for SWC was negative (0.6668) significantly different from zero, which means it had a risk reducing effect. This explains why SWC practices had a higher adoption in low rainfall areas (Table 2). Where they represent appropriate strategies to adapt for climate change in low-rainfall areas.

CONCLUSION AND RECOMMENDATION

Findings of this study provide a consistent answer that climate change adaptation is a successful risk management strategy that makes the adapters' more resilient to current environmental risk. However, the results have demonstrated that although most of the selected farm technologies have significant, positive mean impacts on yields, they do not all show a correspondingly similar risk reducing effect under different rainfall patterns, which might explain their varied adoption rates in these areas as presented in Table 2.

Overall, for all the three rainfall patterns inorganic fertilizer and improved maize seeds appear to be the most important measure for increasing the mean maize yield and risk reducing effects on production. Soil and water conservation appear to be useful investments in high and low-rainfall areas with a risk-reducing effect on production; while intercropping grains with legumes do not seem to have any significant effects on reducing production risk in the lower rainfall areas. On the basis of these results the study concludes that improved farm technologies have significant impacts on reducing production risk in Tanzania and should be strengthened in country's climate-proofing strategy. Since these technologies perform differently in different rainfall patterns, then a one-size-fits-all recommendations is not appropriate, given the differences in agro-ecology and other confounding factors. The performance of these technologies is location specific. Hence programmes aimed at promoting these technologies measures as part of a strategy to adapt to climate change should acknowledge these differences.

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