Adoption of a New Maize and Production Efficiency in Western Kenya

By

Mignouna, D.B.; Mutabazi, K.; Senkondo, E.M.; and Manyong, V.M.

Contributed Paper presented at the Joint 3rd African Association of Agricultural Economists (AAAE) and 48th Agricultural Economists Association of South Africa (AEASA) Conference, Cape Town, South Africa, September 19-23, 2010.

Adoption of a New Maize and Production Efficiency in Western Kenya

D. B. Mignouna[ab,†], K. Mutabazi[a], E. M. Senkondo[a], V. M. Manyong[b]

[a]*Department of Agricultural Economics and Agribusiness, Sokoine University of Agriculture (SUA), P.O. Box 3007 Morogoro, Tanzania.*

[b]*International Institute of Tropical Agriculture (IITA), P.O. Box 34441, Dar es Salaam, Tanzania.*

Abstract

Declining yields of maize as a result of *Striga* infestation has necessitated a new technology known as *Imazapyr*-resistant maize (IRM) to contain the problem. As a result, research and development initiatives with substantial participation of the private sector to transfer this new technology to farmers have been made in western Kenya. This study therefore assesses the adoption of IRM variety and efficiency levels of farmers in western Kenya. A multi-stage sampling technique was used to select a total of 600 households from Nyanza and Western provinces for this study. Tobit model and stochastic production frontier analysis were the analytical methods. Results show that age, education, maize production gap, risk, contact with extension agents, lack of seeds, membership in social group, effective pathway for IRM dissemination and compatibility of the technology are the variables that were found to be significant ($P<0.05$) in shaping the decisions of households on whether to adopt or not. The study reveals that the mean technical efficiency of maize production of sampled farmers is 70% indicating some inefficiencies of maize production in western Kenya. Also, adoption of IRM significantly increased frontier maize output ($P<0.01$); household size decreased inefficiency along with farm size. It was recommended that efforts to increase adoption of IRM for enhanced farm efficiency should focus on farmers' education, farming experience and access to information and farm basic inputs.

Keywords: IRM technology, efficiency, stochastic production frontier, Tobit model.

[†] Corresponding Author: Tel.: +255-78-6960907/+255-23-2603511/4; Fax: +255-23-2600968
E-mail address: mignon_001@yahoo.fr (D. B. Mignouna)

1. Introduction

Striga sp. commonly known as witchweed causes in Africa an annual grain loss of about 8 million tons (Gressel *et al*., 2004) and severely constrains in sub-Saharan Africa efficient and profitable production of maize, *Zea mays L.*, a major food and cash crop to majority of the smallholder farmers. In Kenya, *Striga* infestation is most severe in Nyanza and Western provinces (Manyong *et al*., 2008a) where continuous decline in maize yields was consequence of decreasing soil fertility and increasing *Striga* infestation.

In western Kenya maize is a staple food of great socio- economic importance and *Striga* has been identified by farmers as one of the most important problem in maize production. *Striga* control technologies entailing traditional and novel ones such as push-pull that have been transferred to farmers over decades have failed to contain the problem. Therefore has emerged a new technology known as *Imazapyr*-resistant maize (IRM) involving coating maize seeds with a systemic herbicide called *Imazapyr.*

This study derives its justification from the fact that maize is the main staple food among rural households in western Kenya. However, there has been a decreasing trend in maize production over the last decade due to *Striga* infestation which threatens household food security. Secondly, in the last two decades, maize has had more success in adoption of new technologies that has increased smallholder maize production and in Africa the spread of new technologies has been more important for maize than other food crops. This could provide lessons for further increasing maize production. Assessing of farmers efficiency in maize is resulting from IRM technology adoption which also has some food security implication. Policy makers will therefore be advised on socio-economic, physical and technology variables that influence IRM variety adoption in order to raise the production efficiency and eventually farmers' livelihoods.

Rogers and Shoemaker (1971) have defined adoption as the decision to apply an innovation and to continue using it. Most of previous studies have found that economic variables are major determinants of technological change and of adoption of innovations (Griliches, 1957, 1960). However, adoption and dissemination can also be considered a function of the technological factors (cost, ease of use, expected benefit), of farm specific factors (*Striga* pressure, aversion to risk and farm size); households specific factors (wealth, age, gender, education, household size) and institutional factors (access to agricultural services and inputs) (Chaves and Riley, 2001; Sheikh *et al*., 2003; Lemchi *et al*, 2006; Qaim, 2006). Ouma *et al.* (2002) examined the adoption of Maize Seed and Fertilizer Technologies in Embu District, Kenya and the findings showed that agroecological zones, gender, manure use, hiring of labor, and extension were statistically significant in explaining adoption of improved maize variety.

This study intends to identify physical, socioeconomic and technology factors affecting adoption decision of IRM technology, as well as evaluating the efficiency differentials across the different groups of farmers. In the remaining parts of the paper, section 2 discusses the materials and methods, section 3 itemized the results and discussion, while section 4 concluded with some recommendations that can contribute to increased adoption of IRM technology.

2. Material and methods

2.1 Study area

The study was carried out in Nyanza and Western provinces in the Lake zone of Kenya where maize is the major food and cash crop for small-scale farmers. *Striga* constitutes the most important biological constraint to cereal production and accounts for more than 50% of yield losses and is causing huge damage to maize with losses of more than 182,000 tons per year worth over $29 million. Nyanza province occupies a total area of 12,547 km2 with about 968,014 households as per the 1999 census for a population density of 350 persons/ km^2 while Western province has also a high population density of 406 persons/ km2 on a total area of 8,264 km2 with about 701,323 households (Republic of Kenya, 2001).

2.2 Source of Data

The data used for this study were collected between September and December, 2008 using a structured questionnaire to obtain socio-economic factors, adoption of improved IRM seed, use of land, input use and output as well as IR maize overall performance.

A multistage sampling procedure was adopted for this study to get the total sample size. The first stage involved the purposive selection of two provinces (Nyanza and Western) and three districts per province based on their importance in maize production and high levels of *Striga* infestation. The second stage involved a random selection of 100 respondents sub-stratified into adopters and non-adopters from each of the six districts using the lists of households obtained from the front-line extension workers (FEWs) in Kenya. Therefore a total of 600 households were envisaged good for use in the study

2.3 Methods of Data Analysis

The Tobit Model: Factors influencing adoption of the novel IRM were estimated using some socio-economic, demographic and farm-level agronomic variables of the farmer. The Tobit regression analysis has been used with share of maize land under IRM variety considered as dependent variable and can be expressed as:

$$y_i = x_i\beta + u_i: \qquad \text{If } x_i\beta + u_i > 0$$

$$= 0 \qquad \text{If } x_i\beta + u_i \leq 0$$

$$i=1,2,\ldots.n$$

y_i contains either zeros for non-adopters or a positive area under an improved variety. The model combines aspects of the binomial probit for distinction of $y_i = 0$ versus $y_i > 0$ and the regression model for $E[y_i \mid y_i > 1, x_i]$ where:

y = the proportion of crop area allocated to IRM variety, β = vector of parameters to be estimated; and u_i = error term

The empirical model of the effects of a set of explanatory variables on the adoption of IRM variety applying the maximum likelihood estimation technique is specified using the following linear relationship:

$$Y_k = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + u$$

Where:

Y_k= share of maize land under IRM variety, β_0 = constant.

X_1 = AGE: age of household head (years), X_2 = GEN: gender (dummy: 1=female and 0=male), X_3 = EDU: education in years of schooling (years), X_4 = HSIZE: household size (number), X_5 = FSIZE: farm size (number), X_6 = MPGAP: maize production gap (surplus or deficit in kilogram), X_7 = RRISK: response to risk (dummy: 1= risk takers and 0=risk averters) X_8 = CEXT: contact with extension agents (dummy: 1=contact during the year and 0=otherwise), X_9 = CRED: access to credit (dummy: 1=access and 0=otherwise), X_{10} = LSEED: lack of IRM seeds, X_{11} = MBER: Membership in social group (dummy: 1=existence and 0=otherwise), X_{12} = PATH: pathway in dissemination IRM (dummy: 1=effective and 0=otherwise) , X_{13} = COMPL: complexity of the technology (dummy: 1=simple and 0=otherwise), X_{14} = COMPA: compatibility of the technology (dummy: 1=appropriate and 0=otherwise), X_{15} = PBEN: perceived benefit (dummy: 1=positive and 0=otherwise),.

Stochastic Frontier Production Function Analysis: In order to determine the maize production efficiency, we employed the stochastic frontier model which was estimated using FRONTIER 4.1 statistical software developed by Coelli (1994). It has the advantage of allowing simultaneous estimation of individual technical efficiency of the respondent farmers as well as determinants of technical efficiency (Farrell, 1957; Ajibefun and Abdulkdri, 2004). This study used the (translog) stochastic frontier production function which is of the form:

$$\ln Y_i = \beta_0 + \sum_{k=1}^{K} \beta_k \ln(X_{ki}) + \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{K} \beta_{kj} \ln(X_{ki}) \ln(X_{ji}) + v_i - u_i$$

Where:

ln denotes the natural logarithm; Y_i is the quantity of maize output of the i-th farmer; X is a vector of the input quantities (land, labour, seed, fertilizer, manure); β is a vector of parameters; $k=j=1,\ldots,K$ are input variables;

v is a random error term, assumed to be independently and identically distributed as N (0, σ_v^2), independent of u, which represents technical inefficiency and is identically and independently distributed as a truncated normal, with truncations at zero of the normal distribution (Battese and Coelli, 1995). The maximum likelihood estimation of the production frontier yields estimators for β and γ, where $\gamma = \frac{\sigma_u^2}{\sigma^2}$ and $\sigma^2 = \sigma_u^2 + \sigma_v^2$. The parameter γ represents total variation of output from the frontier that is attributed to technical inefficiency and it lies between zero and one, that is $0 \leq \gamma \leq 1$.

Battese and Coelli (1995), proposed a model in which the technical inefficiency effects in a stochastic production frontier are a function of other explanatory variables. In their model, the technical inefficiency effects, *u*, are obtained by truncation (at zero) of the normal distribution with mean, μ_i, and variance, σ_u^2 such that:

$$\mu_i = Z_i\,\delta$$

Where:

Z is a vector of farm-specific explanatory variables, and δ is a vector of unknown coefficients of the farm-specific inefficiency variables. For the investigation of the farm-specific technical efficiencies of maize producers in western Kenya, the following translog stochastic frontier production function was estimated:

$$
\begin{aligned}
\ln(\text{maize output}_i) = {} & \beta_0 + \beta_1 \ln(\text{Land}_i) + \beta_2 \ln(\text{Labour}_i) + \beta_3 \ln(\text{Seed}_i) + \beta_4 \ln(\text{Fertilizer}_i) \\
& + \beta_5 \ln(\text{Manure}_i) + \beta_{12} \ln(\text{Land}_i)\ln(\text{Labour}_i) + \beta_{13} \ln(\text{Land}_i)\ln(\text{Seed}_i) \\
& + \beta_{14} \ln(\text{Land}_i)\ln(\text{Fertilizer}_i) + \beta_{15} \ln(\text{Land}_i)\ln(\text{Manure}_i) \\
& + \beta_{23} \ln(\text{Labour}_i)\ln(\text{Seed}_i) + \beta_{24} \ln(\text{Labour}_i)\ln(\text{Fertilizer}_i) \\
& + \beta_{25} \ln(\text{Labour}_i)\ln(\text{Manure}_i) + \beta_{34} \ln(\text{Seed}_i)\ln(\text{Fertilizer}_i) \\
& + \beta_{35} \ln(\text{Seed}_i)\ln(\text{Manure}_i) + \beta_{45} \ln(\text{Fertilizer}_i)\ln(\text{Manure}_i) \\
& + \beta_{11}\, 1/2 \ln(\text{Land}_i)^2 + \beta_{22}\, 1/2 \ln(\text{Labour}_i)^2 + \beta_{33}\, 1/2 \ln(\text{Seed}_i)^2 \\
& + \beta_{44}\, 1/2 \ln(\text{Fertilizer}_i)^2 + \beta_{55}\, 1/2 \ln(\text{Manure}_i)^2 + \alpha_1(\text{Mechd}_i) \\
& + \alpha_2 (\text{IRM adoption}_i) + \lambda_1 (\text{Nyanza}_i) + \lambda_2 (\text{Western}_i) + v_i - u_i
\end{aligned}
$$

The dependent variable is (log of) maize output in kilograms. There are three categories of independent variables. The first category includes conventional factors of production: land planted with maize in hectares, labour in man-days, seed planted in kg, fertiliser in kg, and manure in kg. The second category includes mechanization dummy (1= mechanized and 0= otherwise) and IRM adoption (1=adopt, 0=otherwise) to account for intercept shifts in the production frontier due to IRM technology. In order to account for possible gender yield differentials in frontier maize output in the form of an intercept shift of the frontier. The third category includes province dummies to account for the influence of land quality and agro-climatic variations on maize production. The error term, *v*, is the symmetric random variable associated with disturbances in production; and *u* is a non-negative random variable associated with technical inefficiency and is obtained by truncation (at zero) of the normal distribution with mean, μ_i and variance σ_u^2, such that:

$$\mu_i = \delta_0 + \delta_1 \text{ (Education}_i) + \delta_2 \text{ (Farm experience}_i) + \delta_3 \text{ (Farm experience-squared}_i)$$
$$+ \delta_4 \text{ (Household size}_i) + \delta_5 \text{ (Household size-squared}_i) + \delta_6 \text{ (Farm size}_i)$$
$$+ \delta_7 \text{ (Farm size-squared}_i) + \delta_8 \text{ (Gender}_i)$$

Where:

δ_i, '*s* are unknown parameters to be estimated. In view of considerable involvement of the sample farmers in terms of gender, a gender dummy variable was included to test its effect with maize production.

3. RESULTS AND DISCUSSION

3.1 Socioeconomic Characteristics of Households

Table 1 shows a few demographic and socioeconomic characteristics of more relevance in adoption decisions of sampled households for adopters and non-adopters. About 74% of households in western Kenya were headed by male as in most sub-Saharan Africa countries.

The average age of the heads of households for IRM adopters was significantly higher than that of non-adopters adopters of IRM with adopters more literate than non-adopters and this could have facilitated them enough in the adoption of IRM that required comprehension of technical extension leaflets and handbooks. Most empirical studies find that larger farms are more likely to adopt new agricultural technologies than smaller ones. Land holdings are very small in size and farm size is found negatively related to farmers' decision to adopt IR maize technology, non-adopters had more land (1.01ha) than adopters (0.85ha).

Farmers are engaged in different income generating activities, and the main sources of income is crop and livestock selling, and information on household income was captured for the both seasons and was calculated at an average of Kshs 53,719 per household, with the income indicating that adopters of IRM technology had significantly higher household income than non-adopters ($P < 0.05$). This suggests that, adoption of IRM technology was associated with high household income probably due to higher purchasing power to support all the costs requirements for IRM cultivation. The per capita household income corresponded to about US$ 0.51/day for IRM adopters and US$ 0.32/day for non-adopters, characteristic of extreme poverty in western Kenya which is defined as under the World Bank poverty line of US$ 1/day/person.

Extension services are one of the prime movers of the agricultural sector and have been considered as a major means of technology dissemination. Visits by extension agents to farmers and participation of the latter in field days, tours, agricultural shows or seminars are cost effective ways of reaching out with IR maize technology. Regarding the visits, which were paid by extension agents, 41% of households in western Kenya declared receiving at least one visit by extension agents; about 78% were adopters and only about 27% were non-adopters illustrating the low output of extension services which most probably impacted negatively on adoption decision.

Table 1: Socio-economic characteristics of sample households

Statistics	IRM adopters	Non-adopters
Average age of HHH	48.9 (11.5)	45.1 (12.6)
Average years HHH spent at school	6.8 (3.7)	4.4 (3.1)
Average Total land holding	0.85 (0.50)	1.01 (0.54)
Average land allocated to maize	0.41 (0.27)	0.47 (0.29)

Average HH income (Kshs)	80972 (55497)	43033 (41931)
Per capita HH income (Kshs)	13,060	8,119
Per capita per day HH income (US $)	0.511	0.318

N=Number of respondents, HH=Household, HHH=Household head
Figures in brackets indicate the standard deviation

3.2 Factors influencing adoption of IRM technology

The results from the Tobit model used to determine factors influencing adoption of IRM variety using maximum likelihood estimation were presented in Table 2. Since the main purpose of the model was to identify the main factors that influenced adoption of IRM, the model is appropriate for the purpose of considering its significant model chi-square ($p<0.001$), Log Likelihood ratio as well as Goodness of fit, which is generally measured by Pseudo R^2 in such model was 0.96, which showed the soaring predictive ability (Table 2). The coefficient of lack of IRM seeds for planting (LSEED) was significant ($P<0.05$) and negatively related with adoption of IRM. This agrees with the *a priori* expectation and suggests that households lacking IRM seeds for planting had a lower probability of adopting IRM. Farmers lack this suitable and efficient maize variety for *Striga* control, were then left with no choice rather than continuing using the available seeds mostly not even certified. This confirms the empirical work by Griliches (1957) and Heisey *et al*. (1998) that highlighted that farmers without adequate supply of hybrid seed, any successful adoption cannot occur.

Also the coefficient of maize production gap per capita (MPGAP) was statistically significantly ($P<0.10$) and agrees with the hypothesized sign that the surplus of maize production per capita influence adoption of IRM negatively or the deficit of maize production per capita influence positively adoption. Any household in maize deficit has to seek for improved yielded maize variety to increase its production and therefore will adopt IRM. This result confirms the scientific studies have shown the existence of substantial opportunities of increasing food production per capita through the use of improved technologies (Sen, 1996). Appropriate agricultural technologies help to increase agricultural output thereby increasing access to food for the consumers through supply-demand mechanism (Sen, 1996; Foster and Leather, 1999).

The results of the model as depicted in Table 2 suggest that the age of household head (AGE) comprising older farmers adopt IRM more than young farmers as witnessed by the positive and high significant coefficient ($p<0.01$). This may be explained by the fact that aged farmers have accumulated experiences from maize cultivation in *Striga* infestation area over years and could make a difference between past technologies used for its control and IRM variety. There may be a possibility that, IRM may be perceived by high resource farmers as superior technology specific for their area. This goes in line with the finding of Rao and Rao (1996). It is also expected that experienced farmers may be able to understand the nature of risk associated with IRM variety, having seen similar technologies used over time

Furthermore, the adoption of IRM significantly increased ($p<0.01$) as the years of education (EDU) increase. Lawal *et al*. (2004) reported similar finding revealing that exposure to education increases farmer’s ability to obtain, process and use information relevant to adopt IRM for increased yield. The coefficient of education was expected positive to decrease risk aversion behaviour and increase the rate of adoption.

Also the decision to adopt IRM is high significantly influenced by the contact of farmers with extension agents (CEXT). Results of the Tobit analysis show that the contact of a farmer with an extension agent has a positive significant relationship with the adoption of IRM ($P<0.01$). This is a common expectation in the adoption studies where farmers are always seeking for improved technologies which could consequently improve their yield and only extension agents could help farmers to attain their goals by bringing to them the information and demonstrations, source of awareness.

Awareness is critical factor that influencing adoption of innovations that farmers need to integrate themselves into social groups where the communication among individuals within the group is easy. This explains the significant positive relationship ($P < 0.01$) between membership in social group (MBER) and the adoption of IRM. The positive coefficient suggests being in a social group has higher likelihood of adopting IRM and could be the beginning of its adoption process including developing interest and searching for more information necessary for using the innovation.

Since adoption decisions usually involve an element of risk, response to risk and attitude toward risk will influence adoption and the coefficient of response to risk (RRISK) is statistically high significant ($P < 0.01$) and in agreement with the hypothesized positive relationship. This implies that farmers who are risk takers are likely to adopt IRM and will adopt it earlier in the continuum of adoption as depicted Rogers (1995) through the individual innovativeness theory. The expectation of risk taking leads to a higher likelihood of adopting

IRM technology. This finding is in harmony with the studies reported since 1967 of the Popielarz (1967) and Arndt (1967) who agree that willingness to take risk tends to lead to more innovativeness. They concurred that differing attitudes toward perceived risk appears to be the most significant feature in distinguishing adopters from non-adopters. As reported Saha (2001), farmers' perception of risk are associated with lack of information and incomplete learning about new technology and also, high-yielding varieties such as IRM are more sensitive to farm managerial-specific factors compared to traditional seed types. This consists with the view that IRM technology involves greater risk compared to traditional varieties. Risk has often been considered as an important factor reducing the rate of adoption of any kind of innovation. So, risk associated to IRM technology is not always related to the high-yielding varieties technologies but also in practice is highly dependent to the mentioned factors, the matter of which is ignored by most of the previous studies (Feder *et al.*, 1985; Sasmal, 1993; Panell *et al.*, 2000).

Compatibility of IRM (COMPA) was found to have positive relationship with IRM adoption as expected and its coefficient was significant ($P < 0.05$). This suggests that households which perceive IRM as compatible technology for *Striga* control are more likely to adopt it. This finding has been confirmed already by Rogers (1983) and Tornatzky and Klein (1982) who reported that any technology consistent with the existing values of the firms which is aligned with past experience, and matches the needs of potential adopters is positively related to adoption.

Effective pathway of IR dissemination is an important factor influencing adoption of IRM. As expected its coefficient was positive and highly significant at $P<0.01$. The positive coefficient suggests that the use of effective way to disseminate IRM has higher likelihood of adopting it. IRM dissemination in one of most prearranged condition for creating awareness and building the necessary knowledge for using the innovation.

Table2: Tobit model estimates for determinants of share of novel IRM

Variable	Obs	Mean	Std. Dev	Min	Max	Expected sign	Coef	t-ratio
Household specific factors								
AGE	600	0.16	0.287	0	1	-/+	0.0077	3.53***
GEN	600	46.24	12.442	12	81	-	0.0109	0.31

EDU	600	0.26	0.440	0	1	+	0.0197	2.83***
HSIZE	600	5.09	3.436	0	18	-/+	-0.0053	-0.57
Farm specific factors								
FSIZE	600	5.55	2.221	1	13	+	0.0342	0.64
MPGAP	600	0.62	0.485	0	1	-	-0.0001	-2.20**
RISK	600	-27.40	782.271	-1893	2622	+	0.6623	12.48***
Institutional factors								
CEXT	600	0.69	0.462	0	1	+	0.1418	3.49***
CRED	600	0.97	0.536	0.08	4.41	+	0.0202	0.49
LSEED	600	0.60	0.490	0	1	-	-0.2104	-5.18***
MBER	600	0.97	0.161	0	1	+	0.1455	3.32***
PATHW	578	0.70	0.459	0	1	+	0.1561	4.30***
Technological factors								
COMPL	573	0.27	0.442	0	1	-	-0.0234	-0.62
COMPA	573	0.48	0.500	0	1	+	0.1503	2.15**
PBEN	573	0.79	0.406	0	1	+	0.0474	0.99
Constant							-1.0346	-5.95

Significance levels *, ** and *** are $P<0.1$, $P<0.05$ and 0.001, respectively.

Model summary	
Model and estimation	Tobit (censored) and Maximum Likelihood Estimation
Dependent variable	Share of maize land under IRM
Number of observations	573
Software used	STATA
LR chi2 (df)	767.35 (15)
Prob > chi2	0.0000
Pseudo R2	0.9583
Log likelihood function	-16.67
Sigma coef	0.22
Censoring Obs	Left-censored = 404, uncensored =169 and right-censored=0

This study examined the adoption profile of IRM and factors that have driven them. Econometric analyses of factors driving the adoption process gave some levels of reliable statistical accuracy in that the factors considered were important in influencing the adoption decisions of the respondents. The strengths of the impacts of the individual variables included in the models, however, differed. The age, education, maize production gap, risk, contact with extension agents, lack of seeds, membership in social group, effective pathway for IRM dissemination and compatibility of the technology are the variables that were found to be significant in shaping the decisions of households on whether to adopt or not.

3.3 Maize Production and Inefficiency Analysis:

This study used the Maximum Likelihood Estimates for the translog stochastic frontier and efficiency estimations and the results are in Table below. The Table contained the estimates of the parameters for the frontier production function and the inefficiency model and the variance parameters of the model. Results show that the overall mean technical efficiency of maize production farmers is estimated at 70% Therefore, there is a 30% scope for increasing maize production by using IRM technology whose adoption increased maize production by controlling effectively *Striga*. However, TE ranges between 21 to 98 percent among the maize producers in western Kenya.

Also, Table 3 and Figure 1 indicates that 45% of farmers in western Kenya operate at over 75% mean technical efficiency and less than 1% (0.2%) has a mean TE below 25 percent, and thus, is considered technically inefficient with about 14% and 41% of farmers operating at 25-49 and 50-74% respectively.

Table 3: Technical efficiency distributions of maize producers in western Kenya

Technical efficiency (%)	Frequency	Valid Percent	Cumulative Percent
< 25	1	0.2	0.2
25 – 49	79	13.8	14.0
50 – 74	235	41.0	55.0
75 - 100	258	45.0	100.0

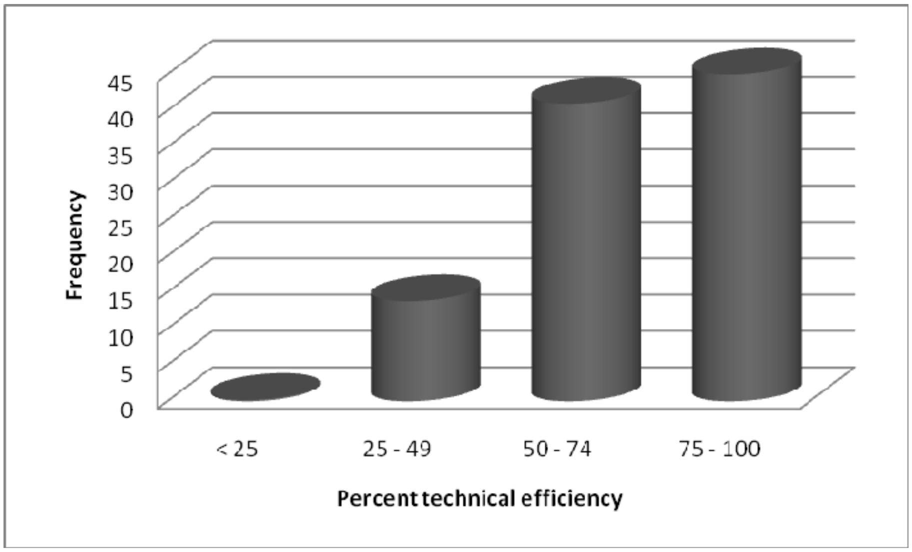

Figure 1: Frequency distribution of technical efficiency for maize production in western Kenya.

Variations in TE of the farmers may arise from their characteristics and the existing technology. Socio-economic variables were considered and estimated in the model and result is presented in Table 4.

Table 4: Parameters of the translog stochastic frontier and inefficiency model for maize production in western Kenya

Variable	Parameter	Coefficients	Std-error	T-ratios
Stochastic frontier				
Constant	β_0	-716.230***	0.605	-1183.892
Land	β_1	1.906***	0.194	9.844
Labour	β_2	-0.153***	0.044	-3.490
Seed	β_3	-0.646***	0.188	-3.429
Fertilizer	β_4	-0.142***	0.055	-2.598
Manure	β_5	-0.306***	0.039	-7.867
Land X Land	β_{11}	0.118***	0.034	3.432
Labour X Labour	β_{22}	0.015***	0.002	6.725
Seed X Seed	β_{33}	0.039	0.032	1.203
Fertilizer X Fertilizer	β_{44}	-0.009***	0.003	-2.847
Manure X Manure	β_{55}	0.030***	0.003	9.310
Land X Labour	β_{12}	-0.013	0.012	-1.090
Land X Seed	β_{13}	-0.197***	0.067	-2.969
Land X Fertilizer	β_{14}	-0.028*	0.015	-1.787
Land X Manure	β_{15}	-0.039***	0.009	-4.092

Labour X Seed	β_{23}	-0.007	0.009	-0.805
Labour X Fertilizer	β_{24}	0.038***	0.004	9.494
Labour X Manure	β_{25}	-0.006***	0.001	-6.140
Seed X Fertilizer	β_{34}	0.048***	0.014	3.411
Seed X Manure	β_{35}	0.082***	0.008	10.592
Fertilizer X Manure	β_{45}	-0.018***	0.004	-4.316
Mechanization	α_0	0.008	0.010	0.779
IR Adoption	α_1	0.218***	0.012	18.841
Nyanza	λ_1	725.844***	0.584	1242.296
Western	λ_2	725.923***	0.585	1241.936
Inefficiency model				
Constant	δ_0	-29.034***	2.284	-12.710
Education	δ_1	-0.071	0.182	-0.388
Farm experience	δ_2	-0.183	0.358	-0.511
Farm experience-squared	δ_3	0.002	0.006	0.388
Household size	δ_4	-57.382***	1.117	-51.360
Household size-squared	δ_5	3.805***	0.097	39.098
Farm size	δ_6	-9.875***	0.986	-10.018
Farm size-squared	δ_7	4.508***	0.602	7.492
Gender (head female = 1)	δ_8	-0.728	0.985	-0.739
Efficiency parameters				
sigma-squared	σ^2	941.526***	1.468	641.164
gamma	γ	0.999999990***	0.000000007	145766790
log likelihood function	LLF	-901		
Mean technical efficiency		0.70		

***Significant at 0.01 level; **Significant at 0.05 level; *Significant at 0.10 level

Source: Field survey, 2007/08

The coefficient of variable representing adoption of IRM is positive and significant at 0.01 level indicating that adoption of IRM increased significantly frontier maize output. This implies that 1% increase in the adoption of IRM variety would increase the yield of maize by about 22%. IRM Adoption increased maize production among the efficient farmers meaning that IRM adoption impacted positively maize production in western Kenya along with other factors to be discovered.

The estimated coefficient for land is positive, which conforms to *a priori* expectation and significant implying that increase in quantity of land would result in increased output. The result could mean that it is possible to expand farming activity in the study area. It may be possible that competition between infrastructure development and crops for land is not yet keen enough to jeopardize the expansion of maize production. Land is therefore, a significant factor associated with changes in output especially in western Kenya where there is a growing population pressure on land. The estimated coefficients for labour, seed, fertilizer and manure were all negative, which do not conform to *a priori* expectation. The negative coefficients of these variable inputs imply that increase in quantities of these inputs would result in decreased output and increased output by continual increasing of the input factors. This may be connected to the fact that the uses of these inputs still insufficient except the use of fertilizer. The use of fertilizer could probably be explained partly by its inappropriate and non-optimal use due to budgetary constraints experienced by the producers. This has been noticed by Kibaara (2005) who also reported the tendency by some maize farmers in the tea-growing region applying tea fertilizer (such as NPK) to maize. Such fertilizer does not benefit maize plants since the nutritional requirement is different. In addition, incorrect timing of the topdressing fertilizer may reduce the effectiveness of the applied fertilizer. Use of top-dressing fertilizer as a basal fertilizer may be another problem. This justifies the observation that only 22% of the surveyed farmers used fertiliser. Moreover, most of these farmers (83%) applied fertiliser below the recommended rates. Low adoption and intensity of use of fertiliser could be associated to the increasing prices of fertiliser relative to maize as reported Manyong *et al.* (2008a). Manure decreases maize output significantly as well as fertilizer and increases the productivity with more quantity. This could be explained by the fact that in addition to the low fertility has been recognized as one of the major biophysical constraints affecting agriculture in western Kenya, intensive and continuous cropping with low application of fertilizer and manure, cause a negative balance between nutrient supply and extraction. Also the relationship between fertilizer application and manure application on maize is inversely related. It is evident that in plots where farmers applied more manure they applied less fertilizer. The alternative explanation would be that as much as farmers apply quantities of inorganic fertilizer, they still believe they would get more productivity by adding small amount of inorganic fertilizer. This is confirmed by the variable "fertilizer-manure" which is negative and significant.

Maize seed is found to be a significant factor influencing changes in maize output in the study area; however, it is negative and significant. Confirming the fact that most of maize seeds planting are not certified with very poor germination rate. By increasing then the factor seeds, it increases the maize output but insignificantly. This confirms the observation that only 21%

of surveyed farmers in western Kenya used certified seeds for planting and the consequence of such practice is low productivity of maize.

Mechanization which is use of oxen or/and tractor for ploughing is positive but statistically insignificant, so increases maize output depicting that very few farmers mechanized the use of land.

The coefficients of the province dummy variables are highly significant indicating substantial maize productivity in western Kenya with Western province slightly greater maize productivity potential than Nyanza province.

Table 4 shows also the results of the inefficiency model. The coefficients of the inefficient variables have the expected signs. Since the dependent variable of the inefficiency function represents the mode of inefficiency a negative sign on an estimated parameter implies that the associated variable has a positive effect on efficiency and a positive sign indicates that the reverse is true. Hence, education, experience, household size, farm size and gender have positive influence on the technical efficiency of the maize farmers. The coefficient of education showed negative and insignificant which indicates that farmers with greater years of formal schooling tend to be more technically efficient indicating that the farmers with more education respond more readily in using the new technology and produce closer to the frontier output. This result is consistent with the idea that schooling increases information and together with long-term experience leads to higher production efficiency (Dey, 2000; Pagán, 2001; Basnayake and Gunaratne, 2002). With education, farmers could be able to read and understand instructions on agricultural innovation and can easily adopt them for enhanced productivity. Positive impact of education on technical efficiency was also observed by Admassie (1999).

The coefficient of experience is estimated to be negative as expected and statistically insignificant indicates that farmers with more experience are found technically more efficient. In other words, the older the farmers are, the more experience they have and the less the technical inefficiency is. Rahman (2002) found similar results in rice farming in Bangladesh. When farm experience is squared, it becomes positive implying that farm technical inefficiency increases with an increase in the number of years in farming of the household head. Therefore this reveals that farm experience enhances farmers' efficiency till a certain given level. This could probably be explained by the fact farmers become more skillful as they grow older and the learning experience by doing effect is attenuated as they approach that level, as their physical strength starts to decline.

Family size reduced inefficiency significantly ($p<0.01$). This implies that consistent availability of labour helps decrease inefficiency by mitigating the shortage of labour. This result is similar to the findings of Parikha and Shah (1994), that family size has positive and significant relationship with efficiency. The findings suggest that the larger the household size, the more cost efficient the household is. A possible reason for this result might be that a larger household size guarantees availability of family labor for farm operations to be accomplished in time. Also, a large household size ensures availability of a broad variety of family workforce which suggests that household heads can rationally assign farm operations to the right person.

The coefficient of farm size is found to be negatively significant in explaining farmers' inefficiency. It indicates that every unity increase in land leads to decrease in technical inefficiency. However, converse result was expected in this regard. Coelli and Battese (1996) observed the same phenomena while studying the technical efficiency of Indian farmers. The advantage of small farms is thus attributed to their greater technical efficiency. According to Admassie (1999), factors other than farm size are more important in explaining the variation in technical efficiency. By progressive increase of farm size, farm size-squared becomes positive and significant at 0.01 level indicating that as its size increases farmers may not be able to maintain the productivity of farm.

The coefficient on the female-headed household variable is negative but statistically insignificant. This could probably be explained by the fact that the female-headed households have greater access to inputs, probably because of their power of gentle persuasion, and hence women could be closer to the frontier because of being more likely more curious, thus willing to attend the agricultural extension training seminars with an aim to discover and know more than they already do.

The determinants of technical efficiency of the maize farmers in the study area include household size and farm size. The implication is that the variables greatly impact on the TE of the maize farmers in western Kenya, which means that the tendency for any maize farmers to increase his production depend on household and farm sizes only at an increased level. Use of IRM on a certain amount of farm size with certified seeds accompanied by proper use of fertilizer and manure is significantly critical for an efficient maize production in the study area. This implies that the more the land is open for production and IRM seeds associated with fertilizer and/or manure used rationally and optimally the more the maize output.

CONCLUSION

Maize is a major food crop in Kenya and the emerging declining trends of maize yields necessitate a study of the factors influencing adoption of IRM variety, guarantee for *Striga* control and technical efficiency in a *Striga* prone area. The policy implications of the findings of the study are hereby discussed.

There is a need to try to change the attitude of farmers by grouping them, so that they start to see each other more as colleagues than as competitors: in this way they will easily share their knowledge and contribute more in new practices diffusion. Farmers in developing countries can become more efficient when they learn from experiences of themselves and their colleagues. Also as extension service popularizes the innovation it is important to provide necessary information, knowledge and skills in order to enable households to apply innovation. Extension will need to build on traditional communication systems and involve farmers themselves in the process of extension. Incentive systems will have to be developed to reward staff for being in the field and working closely with farmers. However education, extension and promotion need to be a coordinated, multifaceted effort involving local government, scientists in various institutions and extension officers. IRM adoption outputs will only be generated if the necessary inputs are made available in the right quantity and at the right time, and with the knowledge of how to implement and use them. However, failure in the seed supply chain for full commercialization of IRM left farmers who needed seed without reliable supply. So the bottom line being the seed, deliberate efforts should be directed to the development of the IRM seed chain by promoting participation of more actors. AATF responsible of IRM deployment in western Kenya should facilitate more IRM seed flows and keep more attention on the viability of seeds produce.

The results showed that adoption of IRM increased significantly maize production. Increased efficiency could be achieved through judicious, appropriate and optimal use of inputs and greater intensity of adoption of IRM technology. Therefore efforts should be made to enhance adoption of IRM and other certified seed varieties. Promoting use of certified seeds and IRM should thus be a critical goal for policy makers in Kenya. In this regard, the novelty of the technology requires a spirit of co-innovation among all the actors involved in IRM variety programs above all MoA, KEPHIS and AATF to help farmers absorb risks by knowing, acquiring and experiencing IRM technology as they already do with the evil *Striga*, so that they could produce closer to their production frontier and reduce hunger and poverty in western Kenya.

Proper ways should lastly be found to extend to the farmers, results of better researches of improved agronomic varieties and practices.

Acknowledgements

The authors are grateful to the International Institute of Tropical Agriculture (IITA), Ibadan, Nigeria for funding this research through a research grant received from AATF, which is also acknowledged for their support.

REFERENCES

Admassie, A. (1999). Sources of Efficiency differentials in smallholder agriculture, *Quarterly Journal of International Agriculture*, vol. 38 (3).

Ajibefun, I.A. and Abdulkadri, A.O. (2004). Impact of size of farm operation on resource use efficiency in small scale farming: Evidence from southwestern Nigeria, Food, *Agric. Environ*., 2(1): 359-364.

Arndt, J. (1967). Role of product-related conversations in the diffusion of a new product, *J. Marketing Res.*, vol. 4, pp. 291–295.

Basnayake, B. M. J. K. and Gunaratne, L. H. P. (2002). Estimation of Technical Efficiency and Its Determinants in the Tea Small Holding Sector in the Mid Country Wet Zone of Sri Lanka. *Sri Lanka Journal of Agricultural Economics* 4: 137-150.

Battese G.E. and Coelli, T.J. (1995). A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics*, 20: 325-332.

Chaves, B., and Riley, J. (2001). Determination of factors influencing integrated pest management adoption in coffee berry borer in Colombian farms. *Agriculture, Ecosystems and Environment* 87:159-177.

Coelli, T.J., (1994). Guide to FRONTIER Version 4:1: *A* Computer Program for Stochastic Frontier Production and Cost Function Estimation. Department of Econometrics, University of New England, Armidale.

Coelli, T.J. and Battese, G.E. (1996). Identification of factors which influence the technical inefficiency of Indian farmers. *Australian Journal of Agricultural Economics*, 40(2): 103-128.

Dey, M.M. (2000). Technical efficiency of tilapia growout pond operations in the Philippines. *Aquaculture Economics and Management* 4 (1/2): 73 - 112.

Farrell, M.J., (1957). The measurement of productive efficiency. J. Royal Stat. Soc., Series A (General), 120: 253-81.

Feder, G., Just R.E. and Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey, *Econ. Dev. and Cul. Ch.*, 33: 255-297.

Foster, P. and Leathers, H.D. (1999). The World Food Problem: Tackling the Causes of Under Nutrition in the Third World. 2nd ed. Lynne Rienner Publisher, UK.

Gbèhounou, G. and Adango, E., (2003). Trap crops of *Striga hermonthica*: in vitro identification and effectiveness in situ. Crop Prot. 22, 395–404.

Gressel, J., Hanafi, A., Head, G., Marasas, W., Obilana, A.B., Ochanda, J., Souissi, T. and Tzotzos, G., (2004). Major heretofore intractable biotic constraints to African food security that may be amenable to novel biotechnological solutions. *Crop Prot*. 23, 661–689.

Griliches, Z. (1957). Hybrid corn: an exploration in the economics of technological change. *Econometrica* 25:501-523.

Griliches, Z. (1960). Hybrid corn and economics of innovation. *Science* 132:275-280.

Heisey, P.W., Morris, M.L., Byerlee, D. and López-Pereira, M.A. (1998). Economics of hybrid maize adoption. In: Morris, M.L. (Ed.), Maize Seed Industries in Developing Countries. Lynn Rienner, Boulder, CO, pp. 143–158.

Kibaara, B.W. (2005). Technical Efficiency in Kenya's Maize Production: An application of the Stochastic Frontier Approach. A Dissertation submitted In partial fulfillment of the requirements For the Degree of Master of Science of Colorado State University Fort Collins, Colorado, 84 Pp.

Lawal, B.O., Saka, J.O., Oyegbami, A. and Akintayo, I.O. (2004). Adoption and performance assessment of improved maize varieties among smallholder farmers in Southwest Nigeria. *J. Agril. Food Inform.*, 6(1): 35-47.

Lemchi J. I, Tshiunza M, Onyeka U and Tenkouano A. (2006). Factors Driving the Adoption of Cooking Banana Processing and Utilization Methods in Nigeria. *African Journal of Biotechnology*, Vol. 8, (11): 1335 – 1347.

Manyong, V.M., , Alene, A.D., Olanrewaju, A., Ayedun, B., Rweyendela, V., Wesonga, A.S., Omanya, G., Mignouna, H.D., Bokanga, M. (2008a). Baseline Study of *Striga* Control using Imazapyr-Resistant (IR) Maize in Western Kenya. An agricultural collaborative study on *Striga* control by the African Agricultural Technology Foundation and the International Institute of Tropical Agriculture. 55pp.

Oswald, A. and Ransom, J.K. (2001). *Striga* control and improved farm productivity using crop rotation. *Crop Prot*. 20, 113–120.

Ouma, J., F. Murithi, W. Mwangi, H. Verkuijl, M. Gethi, and H. De Groote. (2002). Adoption of Maize Seed and Fertilizer Technologies in Embu District, Kenya. Mexico, D.F.: CIMMYT

Pagán, J. A. (2001). *Explaining Technical Inefficiency in Mexico.s micro-enterprises*. University of Texas-Pan American, Edinburgh. 78pp.

Panell, D.J., Malcolm, B. and Kingwell, R.S. (2000). Are we risking too much? Perspectives on risk in farm modeling. *Agric. Econ.* 23: 69-78.

Parikh, A. and Shah, K. (1994). Measurement of Technical Efficiency in the North-West Frontier Province of Pakistan. *Journal of Agricultural Economics*. 45:132.8

Popielarz, D. (1967). An explanation of perceived risk and willingness to try new products, *J. Marketing Res.*, vol. 4, pp. 368–372.

Qaim, M., Subramanian, A., Naik, G. and Zilberman, D. (2006). Adoption of Bt Cotton and Impact Variability: Insights from India. *Review of Agricultural Economics* 28:48-58.

Rahman, K. M. (2002). Stochastic Frontier Analysis: A case of Rice Farming in Bangladesh. Fachbereich Agrarwissenschaften, Ökotrophologie und Umweltmanagement der Justus-Liebig Universität Giessen, Deutschland.

Rao, P.P. and Rao, V.G.K. (1996). Adoption of rice production technology by the tribal farmers. *J. Res. ANGRAU*, 24(1-2): 21-25.

Republic of Kenya, (2001). 1999 population and housing census. Volume 1: Population distribution by administrative areas and urban centres. Central Bureau of Statistiques, Ministry of Finance and Planning. Nairobi, Kenya. 448pp.

Rogers, E.M (1995). Diffusion of innovations (4^{th} ed.). New York. The Free Press. 519pp.

Rogers, EM, 1983. Diffusion of Innovations. Third edition. London: Macmillan. 453pp.

Rogers, E.M. and F.F. Shoemaker, 1971.Communication of innovations: A cross culture approach. The Free Press, Collier Macmillan Publishing Inc. NY. pp: 11-28.

Saha, A. (2001). Risk in HYV and Traditional rice cultivation: An enquiry in West Bengal agriculture. *Ind. J. Agric. Econ.* 56: 57-70.

Sasmal, J. (1993). Consideration of risk in the production of high-yielding variety paddy: A generalized stochastic formulation for production function estimation. *Ind. J. Agric. Econ.* 48: 694-701.

Sen, A. (1996). Economic Interdependence and the World Food Summit. Paper Presented at the Seminar on "Global Food Security" Arranged by Swedish FAO-Committee in Stockholm on 3rd June 1996. Journal of the Society for International Development, available at: http://www.sidint.org/publications/development/96-4b.htm

Sheikh, A.D., Rehman, T. and Yates, C.M. (2003). Logit models for identifying the factors that influence the uptake of new “no-tillage” technologies by farmers in the rice/wheat farming systems of Pakistan's Punjab. 75:79-95.

Showemimo, F.A., Kimbeng, C.A., Alabi, S.O. (2002). Genotypic response of sorghum cultivars to nitrogen fertilization in the control of *Striga hermonthica*. *Crop Prot*. 21, 867–870.

Tornatzky, L. G. and Klein, K. J. (1982). Innovation characteristics and innovation adoption implementation: A meta-analysis of findings, *IEEE Trans. Eng. Manag.*, vol. 29, no. 1, pp. 24–48.