

Full Length Research Paper

Assessing the technical efficiency of maize producers with Imazapyr-resistant maize for *Striga* control in Western Kenya

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Accepted 2 April, 2012

Imazapyr-Resistant Maize (IRM) is a weed control technology, not yet well adopted in the *Striga* prone area in Western Kenya. The adoption may expand in the future because it enhances maize production via efficiency gains. As to help farmers maximize the maize output affected by *Striga* for so long in time, research and development initiatives with substantial participation of the private sector to shift to this novel technology have been made in Western Kenya. A multistage random sampling technique was used to select a total of 600 households from Nyanza and Western provinces for this study. Stochastic production frontier analysis was the analytical method and the study revealed that the mean technical efficiency in the maize production sector is 70% indicating some inefficiencies of maize production. Technical inefficiency effects were influenced by household size along with farm size. Enhancing the technical efficiency will increase net returns of maize production enterprises, hence, improving livelihoods of maize producers.

Key words: Kenya, technical efficiency, stochastic production frontier.

INTRODUCTION

Striga sp. commonly known as witch weed causes an annual grain loss of about 8 million tons in Africa (Gressel et al., 2004) and severely constrains in efficient and profitable production of maize, *Zea mays* L., a major food and cash crop to majority of the smallholder farmers. In Western Kenya, maize is a staple food of great socio-economic importance and continuous decline in maize yields has been identified and reported by farmers as a consequence of decreasing soil fertility and increasing *Striga* infestation being the most important problem in maize production (Manyong et al., 2008).

This study derives its justification from the fact that the

Kenya maize sector has historically been one of its most important farm sectors among rural households in terms of value added and employment. However, important losses in maize production over decades due to *Striga* characterized the maize sector especially, in Western Kenya. The maize losses are estimated to be 182 000 tons per year (Woomer and Savala, 2008). To help the maize sector cope with the losses, *Striga* control technologies entailing traditional like use of farm yard manure or man-pulling and novel ones such as push-pull transferred to farmers have failed to curb the problem (Manyong et al., 2008). Therefore a new technology has emerged known as Imazapyr-Resistant Maize (IRM) involving coating maize seeds with a systemic herbicide called Imazapyr. The results of IRM adoption in Western Kenya revealed that only 28% of the respondents adopted the technology (Mignouna et al., 2011). The

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maize sector is still of high relative importance in the study area and improving the maize sector economic efficiency can be achieved as a result of IRM use and improvement in the economic efficiency of farming operations.

The major objective of this study is to assess the technical efficiency in maize production sector reinforced by the introduction of a new technology - IRM. Specifically, this paper aims to; i) determine the input-output relationships in maize production sector strengthened by the novel technology; ii) evaluate the efficiency differentials across the different groups of farmers; and iii) formulate recommendations towards improving efficiency and profitability of maize enterprise.

Numerous studies have examined the maize production efficiency in Kenya. Recent studies include that of Kibaara (2005), Manyong et al. (2008) and Alene et al. (2008). Kibaara (2005) showed that the overall mean technical efficiency is estimated at 49% in Kenya. Therefore, there was 51% scope for increasing maize production. For Manyong et al. (2008), the adoption of hybrid maize and traditional *Striga* control increased maize production and the sampled maize farmers achieved an average technical efficiency of 62%, indicating a considerable potential (38%) for increasing maize production through improved efficiency and better practices such as integrated *Striga* control. The study by Alene et al. (2008) assessed the relative economic efficiency and output supply and input demand responses of women farmers in Western Kenya and the results showed that women are as technically and allocatively efficient as men. However, neither men nor women have absolute allocative efficiency. Women farmers are equally responsive to price incentives in terms of output supply and input demand. Given the lack of studies of production efficiency of maize producers, the weed pressure confronting the maize sector, and the potential of IRM in the maize production, this study helps understanding the levels of inefficiency/efficiency to address productivity gains if there are opportunities to improve socio-economic characteristics and management practices.

The rest of the paper is subdivided as follows. Subsequently, the study discusses the data design and empirical model used, after which it itemized the results and discussion. Lastly, it concludes with some recommendations that can contribute to increased adoption of IRM technology along with maize producers' efficiency.

Data and empirical model

Western Kenya is the home of over 8 million people and one of Kenya's most densely populated regions (Republic of Kenya, 2001) with a population densities ranging from 300 to 500 persons per km². 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, of which *Striga* seriously constrains

the production, driving farmers into extreme poverty (AATF, 2006).

Data

The data used for this empirical application were collected between September and December, 2008 from 600 households in two districts in Western Kenya using multistage, random sampling techniques. The selection of two provinces and six districts was purposeful rather than random. They were selected based on their importance in maize production and high levels of *Striga* infestation. One hundred households were randomly selected from each district and stratified into two, namely; users of IRM and non-users. The design and data collection was carried out under the supervision of the corresponding author by trained enumerators who had experience with the districts surveyed. Information from these households was gathered through structured survey questionnaires and observations. From the original 600 households in the survey, 169 households used the novel technology.

Empirical model

There are several functional forms that have been developed to estimate the physical relationship between inputs and outputs and several studies have utilized the stochastic frontier approach to assess technical efficiency in various productions (Aigner et al., 1977; Battese and Coelli, 1995; Battese et al., 1996; Awudu and Huffman, 2000; Awudu and Eberlin, 2001; Gautam and Alwang, 2003; Khairo and Battese, 2005). In order to determine the maize production efficiency, the stochastic frontier model was estimated using FRONTIER 4.1 statistical software developed by Coelli (1996). 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 Abdulkadri, 2004). To avoid linearity biases, this study used the transcendental logarithmic (translog) stochastic frontier production function which is of the form:

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

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; $k = j = 1, \dots, K$ are input variables, v is a random error term assumed to be independently and identically distributed as $N(0, \sigma_v^2)$, 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.

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

Table 1. Socio-economic characteristics of sample households (%).

Variables	Unit	Users (N = 169)	Non-users (N = 431)	t-stat (chi-square)
Age of the HHH	Years	48.92	45.19	3.73***
Gender of HHH (male = 1)	1/0	0.71	0.75	-0.04
Education of HHH	Years	6.81	4.41	2.40***
Farming experience	Years	39.80	16.20	23.61***
HH size	Count	6.22	5.28	0.94***
Farm size	Ha	0.85	0.41	0.44

Statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels; HHH = household head.

normal distribution with mean, μ_i and variance, σ_u^2 such that:

$$\mu_i = Z_j \delta \quad (2)$$

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:

$$\begin{aligned} \ln(\text{maize output}_i) = & \beta_0 + \beta_1 \ln(\text{Land}_i) + \beta_2 \ln(\text{Labour}_i) + \beta_3 \ln(\text{Seed}_i) \\ & + \beta_4 \ln(\text{Fertilizer}_i) + \beta_5 \ln(\text{Manure}_i) + \beta_{12} \ln(\text{Land}_i) \ln(\text{Labour}_i) + \beta_{13} \\ & \ln(\text{Land}_i) \ln(\text{Seed}_i) + \beta_{14} \ln(\text{Land}_i) \ln(\text{Fertilizer}_i) + \beta_{15} \ln(\text{Land}_i) \\ & \ln(\text{Manure}_i) + \beta_{23} \ln(\text{Labour}_i) \ln(\text{Seed}_i) + \beta_{24} \ln(\text{Labour}_i) \ln(\text{Fertilizer}_i) \\ & + \beta_{25} \ln(\text{Labour}_i) \ln(\text{Manure}_i) + \beta_{34} \ln(\text{Seed}_i) \ln(\text{Fertilizer}_i) + \beta_{35} \\ & \ln(\text{Seed}_i) \ln(\text{Manure}_i) + \beta_{45} \ln(\text{Fertilizer}_i) \ln(\text{Manure}_i) + \beta_{11} 1/2 \\ & \ln(\text{Land}_i)^2 + \beta_{22} 1/2 \ln(\text{Labour}_i)^2 + \beta_{33} 1/2 \ln(\text{Seed}_i)^2 + \beta_{44} 1/2 \\ & \ln(\text{Fertilizer}_i)^2 + \beta_{55} 1/2 \ln(\text{Manure}_i)^2 + \alpha_1(\text{Mechd}_i) + \alpha_2(\text{IRM} \\ & \text{adoption}_i) + \lambda_1(\text{Nyanza}_i) + \lambda_2(\text{Western}_i) + v_i - u_i \end{aligned} \quad (3)$$

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, fertilizer and manure used in kg. The second category includes mechanization dummy (1 = mechanized and 0 = otherwise) and the extent of IRM (share of maize land under IRM) which were to account for the intercept shifts in the production frontier was 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 which were to account for the influence of land quality and agro-climatic variations on maize production. The error term, v_i is the symmetric random variable associated with disturbances in production, and u_i 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:

$$\mu_i = \delta_0 + \delta_1(\text{Education}_i) + \delta_2(\text{Farm experience}_i) + \delta_3(\text{Farm experience-squared}_i) + \delta_4(\text{Household size}_i) + \delta_5(\text{Household size-squared}_i) + \delta_6(\text{Farm size}_i) + \delta_7(\text{Farm size-squared}_i) + \delta_8(\text{Gender}_i) \quad (4)$$

Where; δ_i , 's are unknown parameters to be estimated. Education and farm experience are important human capital variables that resources. The effect of experience is usually non-linear, and to account for this effect, both experience and experience-squared

determine the efficiency with which farmers use available were included in the inefficiency model. Farm size and household size were included to account for possible inverse relationships on one hand between farm size and technical efficiency and on the other hand between household size and technical efficiency.

It was hypothesized in this study that the effect of farm size and household size could be non-linear, and hence, both farm size and household size and their variables-squared respectively were included. In view of the considerable involvement of the sample farmers in terms of gender, a gender dummy variable was included to test its effect on maize production.

RESULTS AND DISCUSSION

Socio-economic characteristics of households

Table 1 shows some socio-economic characteristics by IRM use status of sampled households that are often associated with the inefficiency analysis. The analysis of the data shows that there is a significant ($P < 0.01$) mean difference between the age of users and non-users. Average age of sample household head is about 49 years with non-users. Farming experience of the household's head which represent human capital is postulated to have a positive impact on efficiency. This common view of the role of experience in farming results from the fact that it enables access to information. On the average, users had significantly more years of farming experience than non-users. No significant difference was observable in the gender of the household head although, the groups vary significantly in terms of their educational level. The household size is an ambiguous effect. It is associated with the availability of timely labour and in this case, larger families are likely to be more efficient. On the other hand, a larger family with more dependants decrease efficiency in farming due to low supply of farming labour. Table 1 indicates that users and non-users consist of 6.22 and 5.28 persons respectively and the difference is statistically significant suggesting the importance of family size for use of new technologies. No significant difference is observable in total farm size. This simple comparison of the two groups of smallholders suggests that users and non-users differ significantly in some proxies of socio-economic characteristics.

Table 2. Mean values of output and explanatory variables (n = 573).

Variable	Unit	Mean	Standard deviation	Min	Max
Output	Kilogram	1016.44	690.10	35.00	3630.00
Land	Hectare	0.48	0.28	0.02	1.22
Labour	Man-day	24.08	24.89	0.00	112.00
Seeds	Kilogram	13.23	7.52	0.25	35.00
Fertilizer	Kilogram	24.28	21.22	0.00	127.00
Manure	Kilogram	33.32	75.74	0.00	600.00
Education	Year	5.13	3.44	0.00	18.00
Farm experience	Year	23.08	13.55	4.00	70.00
Farm size	Hectare	0.99	0.53	0.08	4.41

Table 2 presents some descriptive statistics pertaining to the sample characteristics of the variables quite revealing and adequate to depict the socio-economic characteristics of households. The parameters of the stochastic production frontier model (Equation 3) and those for the efficiency model (Equation 4) are estimated simultaneously, using the maximum likelihood estimation (MLE) program FRONTIER 4.1 (Coelli, 1996). The results in Table 3 contained the estimates of the parameters for the frontier production function and the inefficiency model and the variance parameters of the model.

Production frontier

The results on Table 3 show inefficiency determinants. The variance parameters σ^2 and γ were found to be highly significant. In particular, the value of γ is 0.99 which implies that the production deviations from the frontier functions are practically due to technical inefficiency. Furthermore, a high value of the natural log for the likelihood functions (-901), which is always negative, means that the observed results were more likely to occur again, implying a high predictive ability of the model. The results of the diagnostic statistics therefore, confirmed the relevance of stochastic parametric production function and the maximum likelihood estimation. The estimated coefficient for use of IRM was positive, which conforms to a priori expectation being highly significant at one percent and showed the strongest positive effect on gross value of maize output per hectare. The use of IRM comes as the most important factor of maize production and its positive effect is consistent with the concept of new enhancing-agricultural technologies. Hence, in such a risky environment, if farmers want to increase technical efficiency in maize production, shifting to IRM use offers ample opportunities. IRM use increased significantly the frontier maize output along with other factors in the production process.

There is a positive and significant relationship ($P < 0.01$)

between land and maize output even while increasing land factor. Land is therefore, a significant factor associated with changes in output especially, in Western Kenya where there is a growing population pressure on land. There is a negative and significant relationship ($P < 0.01$) between fertilizer and maize output even while increasing fertilizer factor. In this regard, maize output is more responsive to land and less responsive to fertilizer, low responsiveness of yield to fertilizer was unexpected. This could be due to negative correlation between this variable and other varietal characteristics not included in the model. It could probably be explained by the inappropriate and non-optimal use of fertilizer due to budgetary constraints experienced by the producers. Maize producers have also been facing increasing prices of fertilizer preventing them from its use as reported by Manyong et al. (2008). This was also noticed by Kibaara (2005) who 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 top-dressing fertilizer may reduce the effectiveness of the applied fertilizer. Use of top-dressing fertilizer as a basal fertilizer may be another problem.

Manure correlated significantly ($P < 0.01$) with low maize output, however increased use of manure increased significantly ($P < 0.01$) the maize frontier output. This means that the rate of application of manure is suboptimal and there is a room for improving productivity by increasing the amount of manure applied in maize farming. Low fertility was 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. Furthermore, the interaction between fertilizer and manure appeared to have a negative effect on the maize frontier output. As reported by some farmers, by lack of means, they did apply in their plots more manure and did reduce more importantly the application of fertilizer

Table 3. 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
Lab our	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 use	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.

rendering the application rates of both manure and fertilizer sub-optimal, hence, they did not maximize output anyhow. This is confirmed by the negative and significant

($P < 0.01$) coefficient of the variable “fertilizer-manure”. Maize seed per unit land was found to be a significant ($P < 0.01$) factor that correlated negatively with maize out-

-put. By increasing then the factor seed, it increases the maize output but insignificantly. Most of the maize seeds planted are not certified with poor germination rate. This confirms the observation that few farmers (21%) in Western Kenya used certified seeds in some situation which may have contributed to low productivity.

The coefficients of the province dummy variables are highly significant ($P < 0.01$) indicating substantial maize productivity difference with Western province being more productive than Nyanza province. The difference is probably due to the fact that the population density was lowered by the HIV/AIDS crisis in Nyanza. The population density of the province was already low (350 persons km^{-2}) compared to that (406 persons km^{-2}) in Western province. Nyanza was unfortunately dogged with a number of socio-economic problems such as poverty, malaria, and a very high prevalence rate of HIV/AIDS destroying the much-needed skills and striking the prime-aged adults. Thus, the most productive segment of the economy either fall ill, die or stop productive work. The relative relevance of resource input is shown in the production estimates in Table 3, the mean technical efficiency (TE) in maize production sector is 70%. Therefore, there is a room for 30% scope for increasing maize production. However, TE ranges between 21 and 98% respectively, among the maize producers in Western Kenya. Variations in TE of the farmers may arise from their characteristics and the existing technologies. Examining the technical efficiency of maize farmers in Western Kenya indicates that 45% of farmers operate at over 75% mean technical efficiency and less than 1% (0.3%) has a mean TE below 25%, and thus, considered technically inefficient with about 14 and 41% of farmers operating at 25 to 49% and 50 to 74% respectively.

Further disaggregation of the whole sample of maize producers into IRM users and non-users indicates that the mean TE in maize production was found to be higher with IRM users (89%) than that with non-users (51%). Both users and non-users would be able to increase their output from the available inputs by about 11 and 49% respectively under perfect technically efficient production condition.

The study revealed that IRM users are more technically efficient than non-users. The significant difference between users and non-users could be attributed to farmers' attempts to adjust their production decisions to cope with the changes in the production by using IRM for *Striga* control whose transfer could have also built and reinforced knowledge component. This could have improved the farming skills of the users. In this case, the difference in TE is attributed to IRM, confirming that there is a significant positive impact of IRM package in maize production in *Striga* prone areas.

Determinants of technical inefficiency

In analyzing the sources of inefficiency from Table 3, two

factors were identified. These were household size and farm size. The coefficient of household size was found to be negative and significant ($P < 0.01$) implying in this case that household size through its presumed positive correlation with the availability of family labour, would have reduced labour constraints on the farm and resulted into more quality labour available for carrying out farming activities in a timely manner, thus, making the production process more efficient. This result is similar to the findings of Parikha and Shah (1994), that household size has a positive and significant relationship with efficiency. The coefficient of farm size was found to be negatively significant ($P < 0.01$) in explaining farmers' inefficiency. It indicated that an increase in land leads to decrease in technical inefficiency. Coelli and Battese (1996) observed the same phenomena while studying the technical efficiency of Indian farmers. Larger farms tend to be efficient but sometimes the advantage of small farms is thus, attributed to their greater technical efficiency.

In this study by progressive increase of farm size, farm size-squared becomes positive and significant ($P < 0.01$) indicating that as its size increases, farmers become more and more unable to maintain the productivity of farm. Efficiency is only assured at a manageable level and not beyond. The coefficient of the education was expected to have a negative sign, assuming that a higher level of education would result in lower inefficiency. Similarly, long years of experience in farming also would have reduced technical inefficiency. As farmers gained more experience, they became better equipped and more knowledgeable in maize farming. Both variables indeed had a negative sign, but neither of the two was statistically significant.

Conclusions

The findings revealed a significant contribution of IRM use to increased technical efficiency in maize production in a *Striga* prone area. In order to operate at a high efficiency in maize production constrained by *Striga*, shifting to IRM, applying economies of size in carrying out farming activities in a timely manner should thus, be important for policy makers and stakeholders of the maize sector in Kenya. In this regard, continuous interventions from stakeholders involved in the development and dissemination of IRM would be of interest to farmers to 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, and this resulted to improved agronomic variety.

ACKNOWLEDGEMENT

The authors are grateful to the International Institute of

Tropical Agriculture (IITA), Ibadan, Nigeria for funding this research through a research grant received from African Agricultural Technology Foundation (AATF), which is also acknowledged for their support.

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