Relative Importance Analysis of the Factors influencing Maize Productivity at Olushandja and Etunda Irrigation Schemes of Namibia: A Secondary Analysis of Data from Farm Household Survey

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Abstract

The main objective of this study was to apply relative importance analysis to determine the main factors that affect maize productivity for smallholder maize farmers in the Olushandja Dam and Etunda Irrigation Schemes, north-central Namibia. According to the analysis the key determinants were labour, consultation with extension service providers, land under maize production, the type of seeds used (local or hybrid), access to credit facilities, the experience in horticultural farming. The results singled out labour as the most important factor in maize production, accounting for 16.4% of the farm level variations in technical efficiencies. Technical efficiency gains as the size of land increases. This probably means that those farmers with small plots applied too much of inputs with respect to the size of their land. Farmers who consult extension services and those trained in good horticultural practices were more technically efficient and credit facilities should be availed to farmers so that they can access farm inputs in time to boost productivity.

Keywords: Relative importance analysis, maize productivity, irrigation farming, small scale farmers, Namibia

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1 Introduction

Namibia is one of the driest countries in the world with unreliable and erratic rainfall patterns, limited water supply, recurring droughts and high temperatures (Kuvare et al., 2008; Newsham & Thomas, 2009). Directly or indirectly, the agriculture sector supports over 70% of the country's population (Namibia Crop Prospects, Food Security and Drought Situation Report 2015). The country's agricultural sector is dominated by livestock farming, followed by crop farming. In 2015 agriculture contributes 3.2% to gross domestic product (GDP) (with livestock contributing, 1.9% and crops 1.3%) (NSA, 2015) making the sector a vital source of livelihood through employment creation, food security, income generation and poverty alleviation.

Maize is an important food source in the country secondary to pearl millet (mahangu), constituting around half (50%) of the total cereal consumption in Namibia (Msangi, 2014). Because of the arid climatic conditions and persistent droughts, maize is grown under both rain-fed and irrigation farming systems as it is cheaper to grow maize under irrigation considering the volume of the cereal produced per hectare compared to pearl millet. Dry land white maize is mainly produced in the maize triangle (Grootfontein, Otavi and Tsumeb), in Omaheke, and in Kavango (East and West) and Zambezi Regions. Maize is produced under irrigation at the Hardap Irrigation Project (near Mariental), the Haakiesdoorn at the Orange River (Karas region), Etunda in Omusati region, and the several irrigation schemes in the Kavango West and East Regions (Uvhungu vhungu, Sikondo, Ndonga Linena, Musese, Shitemo, Shadikongoro and Mashare). Increasing volumes of white maize under irrigation is also produced in the Stampriet, Tsumeb, Grootfontein, Kombat and Otavi areas and near the Orange River in the far south

The goal of agriculture is to increase production of crops such as maize by increasing their productivity and water-use efficiency (rain-fed or irrigation) and improving food security through development, adoption and dissemination of sustainable technology Lucas (2012). However, a study by Charamba and Thomas (2016) has shown that the small holder irrigation maize farmers under the Etunda and Olushandja irrigation schemes are operating below the production frontier with an average technical efficiency of 0.433 implying that the remaining proportion of 0.567 is due to inefficiencies and hence maize productivity can be improved by 56.7% utilizing the same inputs and technologies if all the farmers operate on a production frontier. Gamtessa (2014) noted that most farmers exhibiting technical inefficiency or are not operating on the production frontiers such that they could improve their productivities without an improvement in technologies.

Many agro-ecological and socio-economic factors can affect the production of maize and other horticultural produce under irrigation farming in Namibia. For example, water scarcity, soil fertility, the size of land under irrigation, the amount of organic and expensive inorganic fertilizers, pesticides and hybrid seeds as well as unskilled labour force in smallholder irrigation crop production and output market access. In addition, rural households are associated with high poverty levels and income inequality as well as prevalent HIV/AIDS epidemic which can also affect the productive labor force (Sartorius et al., 2014; NSA, 2012a) and this can significantly affect their productivity and malaria which is considered by Masiye and Rehnberg (2005) to have visible impacts on the livelihoods of poor households.

Scholars such as Binan et al, (2004), Kibaara (2005), Msuya et al. (2008) have done studies to estimate technical efficiency and the factors that may lead to technical inefficiencies for small holder farmers. However none of the studies has attempted to rank the magnitude at which these factors really affect productivity so that policy makers and implementers can pay special attention to such factors. The objective of the study was to use the relative importance metrics proposed by Darlington (1968), Lindeman et al. (1980), Pratt (1987) and Feldman (2005) to determine the key factors affecting the farm level technical efficiency for smallholder maize farmers in the Etunda and Olushandja irrigation schemes in North-Central Namibia.

2 Materials and Methods

2.1 The study area and data

The data from farm household survey conducted from May to July 2014 from smallholder farmers producing crops under irrigation systems at Etunda and Olushandja Dam irrigation schemes in the northern-central part of Namibia was used to estimate the farm level technical efficiency in a study by Charamba and Thomas (2016) who used the stochastic frontier analysis method to estimate the farm level technical efficiency for small scale farmers under the two irrigation schemes. The stochastic frontier package of R 3.2.1 statistical software was used to come up with the Maximum Likelihood Estimates of the Cobb-Douglas stochastic frontier production for the farm level technical efficiency (TE). The stochastic frontier method was chosen ahead of the data envelopment analysis (DEA) techniques because it possesses the stochastic aspect which allows it to handle measurement problems and other stochastic influences that would show up as causes of inefficiencies and can handle unmeasured heterogeneity. The estimated efficiencies make the depend variable for this study.

2.2 Method of data analysis

All socio-economic and socio-demographic factors that could possible affect farm-level technical efficiency were considered as predictor variables in the general linear model so that the relative importance analysis technique could then select the most significant factors and covariates from a pools of regressor variables. Descriptive statistics and comparisons of TE for categories the various factors under study were done in IBM SPSS Version 23 (2015). Independent samples T-test was used for comparison of factor levels for binary factors while the Analysis of Variance (ANOVA) techniques was used for comparing category levels for factors with three or more levels. The normality assumption was checked as both tests are parametric in nature. The Levene test for equality of variances was tested and the T-test not assuming equality of variances was employed when the assumption was not met. The R software (Version 3.2.2) **relaimpo** package was used for estimating the relative importance metrics to enable selection of predictor variables that significantly affect the technical efficiency for maize production under the Etunda and Olushandja Dam irrigation schemes. The study used relative importance analysis (RIA) to identify the key determinants of farm level technical efficiency for smallholder maize farmers under the two irrigation schemes. The relative importance metrics computed include the metric *"first"* which looks at what the regressor alone is able to contribute to the dependent variable when it is the only variable in the model, the metric *"last"* which compares what each regressor contributes in addition to all other regressor variables. The study also used the *"pratt"* metric which is a multiplication of the standardized coefficient by the marginal correlations and the metric *"lmg"* which decompose the amount of variability in the response variable (TE) explained by the regression model (R^2) into non-negative contributions that automatically sum to the total R^2.

2.3 Empirical model: Relative importance analysis

2.3.1 The Linear model and the relative importance metric

A general linear model with an intercept and error term can be written as:

$$y_i = \beta_0 + \beta_1 x_{i1} + \sum \beta_p x_{ip} + \varepsilon_i \tag{1}$$

The response variable y_i is modeled as a linear function of regressors $x_{i1} \dots x_{ip}$ with unknown coefficients $\beta_0 \dots \beta_p$ and ε_i is the unexplained error. The measure of the proportion of variation in y that is explained by the model, R^2, is given by:

$$R^2 = \frac{\text{Model SS}}{\text{Total SS}} = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{2}$$

The role of RIA is to partition explained variance among multiple predictors to better understand the role played by each predictor in the general linear model. Metrics used for estimating the relative importance of predictors in this study include the metric first which compares R^2 values for models with each one of the p regressors only, and the metric last which estimates what each regressor contributes when it's added to the model in addition to all the other models available. The relative importance metric last, proposed by Hoffman (1960) and defended by Pratt (1987) is a multiplication of the standard coefficient with the marginal correlation.

2.3.2 The metric lmg

The lmg metric in Gromping (2006) is based on the sequential R^2 but takes care of the dependence on ordering by averaging over orderings using simple unweighted averages.

$$R^2(S) = \frac{\text{Model SS (models with regressors in s)}}{\text{Total SS}} \tag{3}$$

The additional R^2 when adding regressors in set M to a model with regressors in set S is given as

$$SeqR^2\left(\frac{M}{S}\right) = R^2(M \cup S) - R^2(S) \tag{4}$$

The order of the regressors in any model is a permutation of the available $x_1 \dots x_p$ and is denoted by the tuple of indices $r = (r_1 \dots r_p)$. If $S_k(r)$ denote the set of regressors entered into the model before regressor x_k, in the order r, then the proportion of R^2 allocated to regressor x_k in the order r can be written as:

$$SeqR^2(x_k/S_k(r)) = R^2(x_k \cup S_k(r)) - R^2(S_k) \tag{5}$$

Then the metric lmg can be written as:

$$LMG(x_k) = \frac{1}{p!} \sum_{(r\text{permutation})} SeqR^2(x_k/r) \tag{6}$$

Orders with the same $S_k(r) = S$ can be summarized into one summand which simplifies the formula to:

$$LMG(x_k) = \frac{1}{p!} \sum_{S \subseteq \{x_1 \dots x_p\}/x_k)} n(S)!(p - n(S) - 1)! SeqR^2(x_k/S) \tag{7}$$

and Christensen (1992) presented the metric as:

$$LMG(x_k) = \frac{1}{p} \sum_{j=0}^{p-1} \left(\sum_{\substack{S \subseteq \{x_1 \dots, x_p\} \\ n(S)=j}} \frac{SeqR^2(x_k/S)}{\binom{p-1}{i}} \right) \tag{8}$$

The formula shows the lmg as the average over average contributions in models of different sizes.

3 Results

3.1 Descriptive statistics

The results from Table 1 show that although household heads that are employed elsewhere are less efficient compared to those engaging in fulltime farming, the difference is not statistically significant with p-values of 0.289. However, those with access to credit facilities and those who seek extension advice are more productive than those who do not have access to such facilities. Although the difference is not statistically significant at 5% (p-value = 0.100), farmers who have a non-farm business (mean TE = 0.564) seem to be productive when compared to those who have none (mean TE=0.417). The T-test was used after checking for the assumption of normality.

Table 1: T-Test for technical efficiency (TE) comparison for Yes/No Response variables

Attribute	Yes		No		T-test	Levene test
	Mean	S.E	Mean	S.E	p-value	p-value
HHH Employed	0.421	0.030	0.508	0.081	0.289	0.920
Non-farm business	0.564	0.119	0.417	0.028	0.100	0.097
Access to credit	0.490	0.035	0.327	0.041	0.004	0.232
Training in horticulture	0.500	0.068	0.419	0.030	0.265	0.878
Seek extension services	0.502	0.040	0.350	0.034	0.006	0.129
Crop rotation	0.448	0.029	0.206	0.021	0.000	0.019

The results in Table 2 show that married farmers are more technically efficient compared to single farmers and female farmers are more productive compared to their male counterparts. However, the difference is not statistically significant. The use of improved seeds is also more productive. In addition, there is no significant difference between the productivity of farmers under the two irrigation schemes. There is a significant difference between the efficiencies of farmers who implement crop rotation (mean 0.448) and those who do not implement crop rotation (mean = 0.206) as denoted by a p-value of 0.019 which is less than the 0.05 level of significance.

Analysis of variance (ANOVA) was performed after affirming that the underlying assumptions were not grossly violated (value for the Kolmogorov Smirnov test of normality for TE = 0.900 and the error terms for all the ANOVA models considered were independent and normally distributed). Table 3 compares the farm productivity for response variables with

Table 2: T-test for technical efficiency (TE) comparison for other binary response variables

Factor	Response categories	Mean TE	S.E Mean	T-test p-value	Levene's tests p-value
Marital status	Single	0.372	0.045	0.087	0.905
	Married	0.472	0.036		
Gender of HHH[‡]	Male	0.427	0.035	0.721	0.596
	Female	0.449	0.050		
Seed type	Local	0.371	0.093	0.465	0.752
	Improved seeds	0.455	0.032		
Scheme	Olushandja	0.460	0.068	0.629	0.354
	Etunda	0.427	0.031		

[‡]HHH=head of household

more than two categories or responses using the ANOVA techniques. From the results shown, there is no significant difference in the farm efficiency as a result of the highest level of education attained by farmer, the household size and the age of the household heard.

Table 3: ANOVA for technical efficiency (TE) comparison for categorical response variables

Factor	Response categories	Mean TE	S.E Mean	ANOVA p-value
Level of Education of HHH[‡]	None	0.515[a]	0.091	0.899
	Primary school	0.417[a]	0.068	
	Grade 10	0.420[a]	0.050	
	Grade 12	0.457[a]	0.055	
	Tertiary	0.397[a]	0.082	
HH Size	<5	0.386[a]	0.041	0.166
	6-11	0.454[a]	0.039	
	12-17	0.541[a]	0.170	
	>18	0.708[a]	0.128	
Age of HHH	21-30	0.468[a]	0.105	0.958
	31-40	0.401[a]	0.063	
	41-50	0.434[a]	0.047	
	51-60	0.456[a]	0.057	
	61-70	0.382[a]	0.218	
	>70	0.541[a]	0.058	

[a]indicate means that do not differ significantly
[‡]HHH=head of household

The correlation coefficients in Table 4 show that technical efficiency improved with farm size, labour, urea and pesticide and decreases with distance from water source. Addition of manure appears to be insignificant.

Table 4: Correlation between technical efficiency (TE) and continuous variables

Attribute	Correlation coefficient	p-value
Land size	0.420	0.000
Labour	0.478	0.000
Urea	0.340	0.003
Manure	0.080	0.509
Pesticide	0.484	0.000
Years of horticultural practice	0.276	0.020
Number of times of irrigation	0.162	0.178
Distance from water source	-0.014	0.905

3.2 Relative importance metrics

The results in Table 5 are for the relative importance metrics for the 21 factors under consideration as well as the model coefficients. The ten most key determinants of technical efficiency are labour, accounting for 16.4% of the variability in efficiency. Contact with extension services account for 11.2%, land size (9.5%), seed type (8.9%), access to credit facilities (8.5%), use of pesticides (7.9%), number of years in horticultural practice (6.6%), urea used (5.2%) training in horticultural practice and irrigation (5.1%) the number of skilled labours which accounts for 4.5% of the total variability in farm level technical efficiency.

Figure 1 shows the percentage of variations in farm level technical efficiency accounted for by the different factors under study. The lmg metric shows that labour, land size, seed type and access to credit facilities account for the highest proportions in the coefficient of determination R^2, making them the key factors in differentiating farm to farm technical efficiency. The metric last indicates that age of household head, years of horticultural practice, the type of maize seed grown whether local or hybrid, skilled labour, contact with extension services providers and training in horticultural agriculture significantly affect the coefficient of determination when they are entered last into the model with all the other variables.

4 Discussion

According to Kibaara (2009) increasing labour indefinitely while holding the other inputs constant will result in diminishing marginal productivity. The empirical results show that both labour and land size are key factors in increasing technical efficiency, implying that the farmers who grow maize on larger pieces of land utilize more labour and are more economic in resource utilization than farmers growing maize on smaller pieces of land who might be applying too much inputs with respect to their land size. The findings concur with Phillip (2007) whose study on the efficiency of production of crops used in bio-fuels in Tanzania

Table 5: Relative importance metrics and model coefficients

Factor	Importance rank	lmg[‡]	last	first	pratt	Model coefficient
Gender of HHH	18	0.006	0.002	0.005	0.003	0.057
Age of HHH	11	0.029	0.094	0.005	0.024	0.002
HH Size	13	0.027	0.003	0.036	0.013	0.018
Marital status of HHH	17	0.007	0.009	0.006	0.008	0.048
HHH level of Education	15	0.021	0.017	0.020	0.023	0.015
HHH employment status	20	0.004	0.008	0.000	0.002	-0.019
None farm business	19	0.006	0.008	0.006	0.004	0.047
Years of horticulture	7	0.066	0.103	0.055	0.097	0.016
Labour (man-days)	1	0.164	0.068	0.182	0.213	0.063
Seed type	4	0.089	0.097	0.085	0.108	0.155
Land size	3	0.095	0.007	0.125	0.052	0.046
Urea	8	0.052	0.009	0.071	0.029	0.000
Manure	16	0.012	0.068	0.003	0.017	0.000
Pesticides	6	0.079	0.040	0.107	0.091	0.010
Skilled labour	10	0.045	0.087	0.030	0.054	0.064
No of irrigation times	12	0.029	0.000	0.049	0.004	0.022
Distance to water source	21	0.001	0.002	0.001	0.002	0.005
Access to credit facilities	5	0.081	0.074	0.088	0.102	0.235
Contact with extension services	2	0.112	0.107	0.099	0.139	0.242
Crop rotation	14	0.021	0.067	0.009	0.027	0.092
Training in horticulture	9	0.051	0.131	0.021	0.057	0.245

[‡]lmg=; last=; first=; pratt=

confirmed that large land owners are more efficient and Musemwa et al. (2013) found similar results. However, these findings contradicts Peterson (1997) whose study discovered evidence of diseconomies of scale as farm size increases.

Increasing fertiliser input increased maize productivity (accounting for 5.2% of the variations in technical efficiencies). However, the same cannot be said for manure as signified by the negative pratt relative importance metric. These findings contradict the findings of Kibaara (2009) whose studies discovered that technical efficiency increases with both fertilizer and manure. This might mean that the Etunda and Olushandja irrigation farmers are using too much fertility inputs relative to other inputs like land as some are using both organic and inorganic fertilizer on the same plots.

Farmers who use pesticide and agrochemicals are more productive when compared to those who do not spray their maize. According to Lucas (2012) pest management and control is one of the most important factors to promote crop productivity in Namibia. This contradicts the findings from Msuya et al. (2008) who discovered that farmers who use agrochemicals are less efficient than those farmers who do not spray. His study was probably done in an environment not susceptible to pest outbreaks.

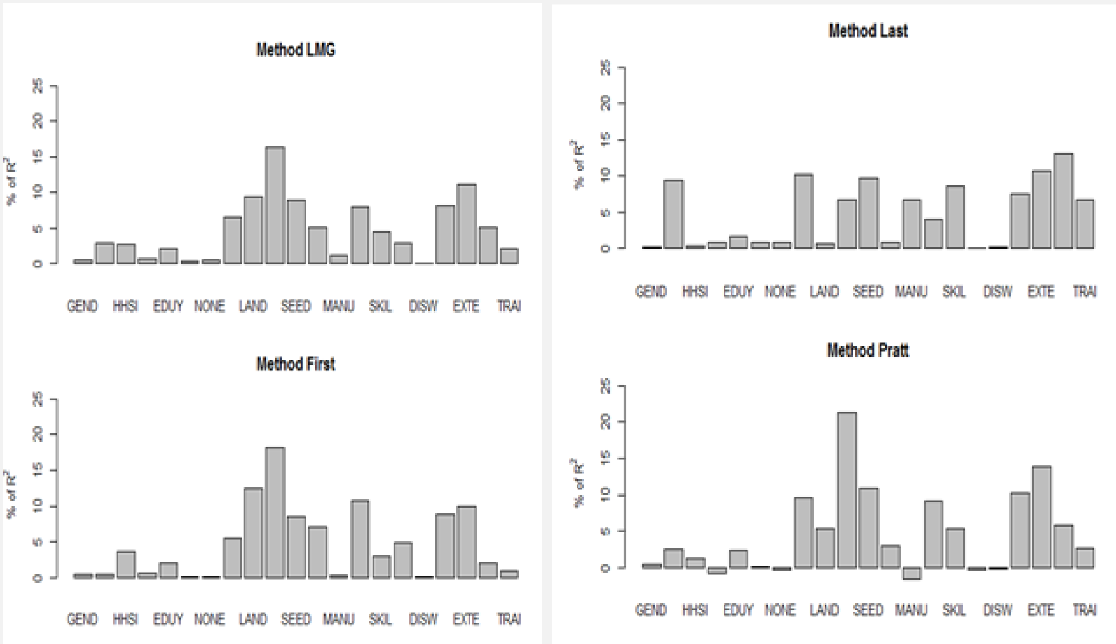

Figure 1: Relative importance metrics for Technical Efficiency, with R^2=60.53%. Metrics are normalized to sum to 100%.

Contact with extension service providers is the second most determinant of the difference in farm productivity, constituting 11.2% of the variation in technical efficiency. With farmers consulting extension service providers more productive. Extension services and training of farmers on horticultural practices have a positive impact on productivity. This shows that knowledge and information are very important factors on farmer productivity. According to Poulton et al., (2010) expectations with regards to the performance of agricultural extension services remain low in developing countries since their delivery faces many limitations and may not lead to improved productivity (Theriault and Serra, 2014) unless the dissemination of information influences farmers to adopt good agricultural practices . There is a wide gap between the technical efficiencies of farmers who use crop rotation and those who use monoculture. This is in agreement with Hulugalle and Scott, (2006) who indicated that farmers who practice crop rotations rather than practicing monoculture are more likely to get higher yields due to better conservation of soil fertility. However, although the results show such a wide gap in efficiencies, the factors was ranked 14 out of the 21 factors under consideration by the relative importance metrics as 95% already practice and only 5% are practicing monoculture agriculture.

Those farmers who use improved maize seed on their irrigation plots were more productive than the farmers who use local seeds for maize production, contributing to 8.9% of the differences in technical efficiency. However, although the study by Charamba and Thomas (2016) concluded that the farmers that are closer to the water source are more productive basing on the sign of the coefficient of the stochastic frontier model, the results from the relative importance analysis indicated that the difference is not that significant, with the factor being ranked last. However, the number of times of irrigation was not a significant factor on technical efficiency in maize production probably the maize farmers' level of irrigation does not differ much.

The difference in the number of years of horticultural practice accounted for 6.6% of the differences in the small scale farmer productivity, with older farmers being more productive, supporting the findings of Musemwa et al. (2013) who argue that older farmers are more efficient. However, the ANOVA results and the results from the stochastic frontier analysis (Charamba & Thomas, 2016) render the differences insignificant. Theriault and Serra (2014) found that farmer experience on cash crop such as cotton farming negatively influences efficiency.

The level of one's formal education did not contribute much (accounting for 2.1%) to variations in efficiency in maize production, an agreement with the stochastic frontier findings where the effect was statistically negligible. This is probably because most (67 out of 78 or 86%) of the farmers only attended school for less than 10 years and 28 out of 78 or 36% did not attended formal education. According to Gebremedhin et al. (2009) and Nkhori (2004) educated farmers are assumed to have better farming capacity and access to information and thus considered to be more efficient.

The descriptive results show that technical efficiency increases with household size although the ANOVA results renders the difference insignificant. Household size is ranked thirteen on the relative importance scale accounting for 2.7% of the differences in farm level productivity. Although the proportion of variability it accounts for is small, households with more members are more productive. These findings are in agreement with Feder (1985) who found out that increase in household size result in increased labour and less dependency on hired labour as family labour is more efficient. Montshwe (2006) also argue the large households are more productive as resources pooled, income is shared and ideas are pooled in joint decision making.

From the findings of the study, the age of the farmers accounted for 2.9% of the variability in technical efficiencies (ranked 11) with older farmers being more efficient. These findings support the results of Binam et al. (2004), who argue that the older the farmer, the greater the experience and in turn the efficiency. Binam et al. (2004) also argue that young farmers are deficient in resources and might not be able to apply the inputs or implement agro practices efficiently. However, the ANOVA results from this study and the stochastic frontier findings in Charamba and Thomas (2016) render the differences statistically insignificant.

Access to credit facilities is one of the most important factors, explain 8.5% of the variation in technical efficiencies for the small scale farmers under study with farmers with access to credit facility being more are more technically when compared to those who do not have such facilities. If farm level credit is properly managed, it enhances diversified systems of agriculture which stabilizes and increase productivity.

Although the effect is statistically insignificant, households that own a non-farm business are more efficient when compared to those who do not own one. These relative importance findings contradict the stochastic frontier finding where households with a non-farm business where less efficient compared to those with none. Maybe households with nonfarm business have more access to capital for farm inputs. Alemu et al. (2009) contradicts this, propounding that the effect of off-farm income on efficiency could be negative if farmers have higher chances of obtaining off-farm and non-farm employment, ultimately reducing the technical efficiency of the farm. However, the factor only accounts for 0.6% of the differences in farm productivity.

According to the T-test results, relative importance results and the stochastic frontier analysis, there is no significant difference in farm productivity for male and female farmers, supporting findings by Tchale and Sauer (2007) who observed a negligible effect of the farmers' gender. Kibaara (2009) found out similar results among smallholder farmers in Kenya.

5 Conclusions

The study findings have shown that knowledge is power in agricultural productivity and hence farmers should be constantly trained on appropriate horticultural practices and encouraged to consult extension service providers in order to boost maize productivity thereby increasing food availability and access. Moreover, access to credit facilities has proved to be one of the key determinants of technical efficiency discrepancies.

The study makes the following recommendations:

- Farmers should be encourage to practice crop rotation
- Farmers need to be trained on efficient use of inputs especially urea and fertiliser so that they apply the appropriate amount with respect to the size of their land.
- Credit facility programmes be availed to the farmers so that they can have more access to farm inputs, thereby increasing their productivity.

Conflict of Interest

The authors declare that there is no conflict of interests regarding this paper.

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