Maize Production Risk and Technical Efficiency in Agricultural Development Programme Zone I of Taraba State, Nigeria

ABSTRACT

This study analyzes maize production risk and technical efficiency in agricultural zone I in Taraba State, Nigeria. The study collected primary data from 299 randomly selected maize farmers during the 2022 farming season. The Cob-Douglas stochastic frontier production functions were used to analyze the data. Estimates of the stochastic frontier production function revealed that the coefficients of seeds, fertilizer, and agrochemicals were significant and positively related to maize output, while labour was negatively related to maize output. The input variables were jointly influencing maize output at decreasing returns to scale. The technical efficiency indices ranged from 0.34 to 0.97 with a mean of 0.75, indicating that the maize farmers in the study area were technically efficient in their production system, although they were operating below the frontier output. The study also revealed that seeds and fertilizer were risk-reducing inputs, while agrochemicals and labour were classified as risk-increasing inputs. The inefficiency model revealed that the technical efficiency of the farmers increased with age, education, extension contact, and land cultivation technique. The study concludes that the farmers were technically efficient, though below the frontier, and there is risk in the input used by the farmers. The study recommends that young educated people should join maize farming in the study area, farmers should use more seeds and fertilizer very well to stabilize output, and the government should encourage extension services and training for farmers.

Key words: Maize: technical efficiency: production risk: SFA: TADP

1. INTRODUCTION

In the continent of Africa, Nigeria is the second-largest producer of maize after South Africa [1]. The states of Taraba, Borno, Niger, Plateau, Katsina, Gombe, Bauchi, Kogi, Kaduna, and Oyo are the top 10 producers of maize in Nigeria. Approximately two thirds (64%) of the nation's maize production came from these states [2]. Poultry farmers in Nigeria use about 98% of the country's animal feed production, which is made from about 45.5% of the country's maize crop. Although 13% of Nigeria's maize crop is used to make industrial flour, corn flakes, and other confections, the remaining 6.5% is utilized by brewing enterprises. However, the percentage of maize consumed in households is only 10% to 15% [2].

Nigeria is the continent's second-largest producer of maize, but its export potential looks small in comparison to peers like South Africa, which exported about two thirds of the continent's maize

[3]. The use of poor maize varieties, which results in poor maize yield, the presence of risk in the production process, climatic changes, and a lack of Good Agronomic Practices (AGP), such as the use of fertilizers, pesticides, and herbicides for efficient soil management and pest control, are the main causes of Nigeria's relatively low maize export. Less than two tons per hectare (t/ha) of maize are produced in Nigeria, compared to 4.9 t/ha and 4.2 t/ha in South Africa and Ethiopia, respectively [4].

Zone I of the Taraba State Agricultural Development Programme (TADP) is known for its inconsistent and low yielding maize production. Even in cases where output rises, it does so only as a result of land expansion. For instance, in 2021, 20.76 thousand hectares of land were cultivated, producing 42.41 thousand metric tons (tmt) of maize with a yield per hectare of 2.04 tons. The yield per hectare fell to 1.55 tons in 2022, despite an increase in production to 44.01 tmt and an increase in cultivated land to 28.23 thousand hectares [5]. Technical inefficiency and cultivation risks lead to variations in maize cultivation, preventing farmers from achieving their maximum output potential [6]. Technical efficiency occurs when a farmer can maximize output using the least amount of inputs [7]. Cultivation risk refers to the fluctuations in output that arise from decisions made about inputs [8].

Numerous academics have studied the technical efficiency of maize production and offered suggestions for increasing potential yield or lowering potential costs. However, [9] and [10]'s usual stochastic frontier, which is used to estimate technical efficiency, is insufficient to account for production risk, a significant factor in production. A partial assessment of technical efficiency will result from failing to take production risk into consideration while utilizing inputs. Policy makers may be misled by these skewed estimates. Thus, the purpose of this study is to assess maize production risk and technical efficiency in Zone I of the Taraba State Agricultural Development Programme in Nigeria.

Conceptual and Empirical Review

Technical efficiency refers to a farmer's ability to maximize output with the fewest inputs [7]. Production risk refers to the variation in output as a result of input decisions of a farmer [8]. The output in the context of this study is the maize grains, and the factor inputs or resources are land, seed, fertilizer, agrochemicals, and labour. In the process of cultivating land, combining seed, fertilizer, agrochemicals, and labour to produce maize grains, farmers in Ardo-Kola LGA of Taraba State are exposed to cultivation risk. This could be either in the choice of using land, seeds, fertilizer, agrochemicals, and labour or the maize grains they intend to produce. The procedure of estimating cultivation risk that brought about differences in the anticipated output and the observed output was proposed by [11]. They recommended cultivation method meeting several required features. The primary recommendation of [11] is to permit inputs add or reduce cultivation risk on the output. The idea of input to add or reduce cultivation risk on the output is beneficial for risk management. However, the method failed to include producers' attitude toward risk. The producer's position on risk is crucial when deciding on inputs allocation this subsequently affect the provision of output supply. Since in realness, input output is decision making variables, it is suitable to look for a method that captures both production risk and producers’ attitude on risk.

The problem was solved by looking at producer’s risk choice in a collective breakdown of input allocation determination and provision of output [12]. Therefore, the idea simply expands [11] method which without doubting presumes input to be given. The straightway challenge in considering producers attitudes toward risk into experimental analysis is that a precise and clear form of utility function has to be adopted. It is also important to make some distributional presumptions on the irregular terms that stand for production risk. Despite these presumptions, the common challenge to practical investigator is the fewness of utility functions and likelihood dispersions that can be utilized to develop the risk procedure by virtue of analysis [13].

The work of [13] put up to existing literature on production risk, risk preferences and technical inefficiency. The author algebraically develops risk preference function not including the presumption of: definite utility function and a precise distributional term that stand for production risk. The author perceived two origins of risk namely; production risk and technical inefficiency. The risk choice function for each origin is developed and measured. The author’s stipulation of risk choice function is common and adequate to take care of constant, decreasing and increasing risk dislike attitude. The procedure give room for producers to be technical and allocative inefficient and demonstrate a way to measure these inefficiencies in a procedure compatible with both production risk and producers attitude toward risk. Studies that used this procedure to estimate production risk and technical efficiency includes: [14], [15], and [16] respectively.

The materials and methodology, which include the study area, theoretical framework, empirical model specification, hypothesis statement, data, and sampling strategy, were briefly presented in the following chapter. The findings are then stated on and discussed. The conclusion and some policy implications are presented in the final section.

2. MATERIALS AND METHOD

2.1 Study Area

The Taraba State Agricultural Development Programme [TADP] Zone I, located in the Ardo-Kola Local Government Area (LGA), encompasses the Iware block. The block contains 8 cells, namely: Iware, Abare, Mallam Aligora, Zongo Kambai, Mallum, Mayo-Renewo, Bakin-Dutse, and Tau. Ardo-Kola LGA lies within latitude 8^0 50'-90^0 10’ North and longitude 11^0 20’ -11^0 25’ East. Karim Lamido LGA borders the LGA to the north, Jalingo LGA to the east, Gassol LGA to the west, and Bali LGA to the south. It has a predicted population of 13,897 people [17] and a land area of 2,262 square kilometers. The LGA is characterized by distinct wet and dry seasons. The wet season starts in April and ends around October. While the dry season lasts for the remaining part of the year. The climate, soil, and vegetation of the LGA allow for the cultivation of staple crops like maize, sorghum, and millet, among others. Residence also raises livestock such as cattle, sheep, and goats.

2.2 Data and Sampling Techniques

This study employed cross-sectional data from a total of 299 maize farms randomly sampled from Taraba State Agricultural Development Programme [TADP] Zone I. The data was collected from a survey that was conducted from March to July 2022 in the eight cells of TADP Zone I, which are Iware, Abare, Mallam Aligora, Zonga Kambai, Mallum, Mayo-Renewo, Bakin-Dutse, and Tau. The data was collected on input and output variables as well as farm-specific variables.

2.3 Statement of Hypotheses

The following hypotheses are considered for investigations

1. The coefficient of the second order variable in the trans-log model are zero thus: $(H_{01} = \beta_{jk} = 0)$

2. The variability in maize output is not explain by the production risk in input use thus:

$(H_{02}: \varphi_1 = \varphi_2 = \varphi_3 = \varphi_4 = 0)$.

3. The exogenous variable do not explain variation in technical inefficiency thus:

$(H_{03}: \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = \delta_8 = 0)$.

2.3 Method of Data Analysis

Descriptive statistics was used to summarized the inputs output variables, while stochastic frontier estimate production risk, technical efficiency level of the respondents as well as the exogenous variables influencing their technical inefficiency level.

2.4 Theoretical Framework

The empirical application of this study is consistent with models developed by [9], [10], [11] and [13]. A generalized Kumbhakar SFA model with a flexible risk specification is specified as:

$$Y_i = f(X_i: \beta_i) + g(X_i: \varphi_i)V_i - q\ (Z_i: \delta)U_i \quad (1)$$

Y_i refers to the observed output produced by the $i - th$ farm, $f(X_i: \beta_i)$ is the deterministic output function, $g(X_i: \varphi_i)$ is the output risk function, φ_i are the estimated coefficients of the production risk function, X_i are the input variables, β_i are the estimated coefficients of the mean output function, $g(Z_i\colon \delta)$ represent the technical inefficiency model, δ are the estimated effect of the explanatory variables in the technical inefficiency model, V_i represents the random noise in the data, representing production risk and U_i represents farm specific technical inefficiencies. Given the values of the inputs, and the inefficiency effects, the mean output of the $i-th$ farmer is given by:

$E(Y_i/x_t\colon u_i) = f(x_t, \beta) - g(X_i\colon \varphi)U_i$ (2).

$TE_i = \frac{E(Y_i/x_i;u_i)}{E(Y_i/x_i;u_i)-0} = \frac{f(x_i;\beta)-g(x_i;\varphi_i)U_i}{f(x_i;\beta)} = 1 - \frac{g(x_i;\varphi_i)u_i}{f(u_i;\beta)}$ (3)

Technical efficiency becomes:

$TE_i = 1 - TI_i$ (4)

The technical inefficiency, TI is represented as:

$TI_i = \frac{g(x_i;\varphi)u_i}{f(x_i;\beta)}$ (5)

The variance of output or production risk is given by:

$Var\ (Y_i/x_i, u_i) = g^2(x_i; \varphi)$ (6)

$\frac{\partial V(Y)}{\partial xj} = \frac{\partial g^2(x,\varphi)}{\partial xj} = 2g(x;\varphi)gj(x,\varphi)$ (7)

Thus, $\frac{\partial g^2(x,\varphi)}{\partial xj} < 0 \leftrightarrow$ Risk decreasing of the jth input

$\frac{\partial g^2(x,\varphi)}{\partial xj} = 0 \leftrightarrow$ Risk neutral of the jth input and

$\frac{\partial g^2(x,\varphi)}{\partial xj} > 0 \leftrightarrow$ Risk increasing of the jth input.

Based on the distributional assumptions of the random errors, a log likelihood function for the observed farm output is parameterized in terms of

$\sigma^2 = \sigma_v^2 + \sigma_u^2\, and\ \gamma = \sigma_u^2/\sigma_v^2 \geq 0$ [6].

2.5 Empirical Model Specification

The empirical application of this study is consistent with the models developed by [13]. The Trans log model is assumed for the deterministic part of the production frontier in equation (1) and presented as:

$liny_i = \beta_0 + \sum_{j-1}^{4} \beta_j lnx_{ji} + 0.5 \sum_{j-1}^{4} \sum_{k-1}^{4} \beta_{jk} linx_{ji} linx_{ki} + \varepsilon_1$ (8)

β_j denotes the unknown true values of the technology parameters. If, $\beta_{jk} = 0$ then the translog stochastic frontier model reduces to the Cobb-Douglas model given as: +

$\varepsilon_i = g(x_i; \varphi)v_i - q(z_i; \delta)u_i$ (9) [18]. The trans-log model was reduced to Cobb-Douglas production function due to its suitability for estimating technical efficiency in our study, easy to calculate elasticities, and the elastic functional form solves the difficulty of multi-collinearity commonly found in trans-log model. The sum total of the output elasticity from the input variables is the estimated scale elasticity (K) which is defined as the percentage change in output as a result of 1% change in all input factors. When K$>$ 1 it means increasing return to scale (IRS), K$<$ 1 decreasing return to scale (DRS), and K =1 implies constant return to scale (CRS). Following [16], the scale elasticity in this study is the frontier output elasticity. Man, days for labour is calculated with the formula: one adult male working for one day (8 hours) equals one man day; one female and one child (<18years) working for one day (8hours) equal 0.75- and 0.5-man days respectively. The calculation of the man days is in line with [14] and [19].

The linear production risk function is specified as:

$g(x_i; \varphi) = \varphi_0 + \sum_{4-1}^{4} \varphi_m x_{mi}$ (10).

Where x_m^s represent the input variables, as described in Table 1. φ_m^s represent the unknow true coefficients of the risk model parameters and v_i^s are the pure noise effects. Where φ_m^s becomes negative, the respective input reduces output variance and vice versa [11]. The technical inefficiency effects are given by:

$q(z_j, \delta) = \delta_0 + \sum_{j-1}^{8} \delta_j z_{ij}$ (11)

Where δ_t^s denote the unknown true values of the parameters of the technical inefficiency model and z_j^s are the exogenous explanatory variables.

Table 1. Description of input variables in the maize production process

Variable	Variable description	Measurement
y_i	Output	Kilograms/hectare
x_{1i}	Seed	Kilograms/hectare
x_{2i}	Fertilizer	Kilograms/hectare
x_{3i}	Agrochemicals	Liters/hectare
x_{4i}	Labour	Man-days/hectare

Note: Land is not included in the variable analysis because all the variables were measured in their respective units per hectare.

Table 2. Description of exogenous variables

Variable	Variable description	Measurement
z_{1i}	Age	Years
z_{2i}	Household size	Number
z_{3i}	Education level	Non- formal 0, Primary 1, Secondary 2, Tertiary 3
z_{4i}	Farming experience	Years
z_{5i}	Extension contacts	Had contact 1, otherwise 0
z_{6i}	Land cultivation technique	Use tractor 1, otherwise 0
z_{7i}	Planting technique	Use machine 1, otherwise 0
z_{8i}	Harvesting technique	Use machine 1, otherwise 0

3. RESULTS AND DISCUSSION

3.1 Summary Statistics of the Output and the Input Variables

The result for this study (Table 3) reveals that on average, farmers used 44.45 kilograms per hectare of seed, 188.47 kilograms per hectare of fertilizer, 5.20 liters per hectare of agrochemicals, and 24.2-man days per hectare of labour in order to produce 1.965 tons per hectare of maize. The minimum and maximum production were 1.64 and 4.08 tons per hectare, respectively. The coefficient of variation for production was 443.2. The average yield of 1.965 tons per hectare of maize indicates that most farmers produce below the maximum yield per hectare. However, considering all the inputs in the production process, the frontier output remains unknown. Therefore, this study aims to estimate the determinants of technical efficiency.

Table 3. Summary statistics of output and input variables

Variable	Unit	Mean	Minimum	Maximum	Std Deviation
Output (Maize Grains	Kg/ha	1964.6	1636	4076	443.2
Seed	Kg/ha	44.45	8.55	68.28	12.24
Fertilizer	Kg/ha	188.47	125	325.15	48.26
Agrochemical	Lt./ha	5.20	1.45	9.70	1.72
Labour	Man-days/ha	24.2	12	38	5.42

Source: Field survey data, 2022

3.2 Summary Statistics of the exogenous variables

The farmers' mean age was 38, with a minimum of 18 and a maximum of 63 years. The age variation was 9.5 years. The average household size among the respondents is 9 individuals, ranging from a minimum of 4 to a maximum of 15 individuals. The household size had a variability of 3 people. About 38.1% of the farmers had up to tertiary education, 23.1% had up to secondary education, and 28.1% had up to primary education, while 10.7% had never had formal education. The respondents' average experience in farming is 15 years, with a minimum of 6 and a maximum of 39 years. The respondents' varying levels of farming experience were calculated to be 4.3. The majority (56.9%) of the respondents had contact with extension agents, while 43.1 had no contact with extension agents. Information on field management revealed that the majority (55.2%) of the respondents cultivate their farmland using tractors (machines), while 44.8% of the respondents use crude implements. All (100%) of the maize producers in the study area used the manual method of planting and the manual method of harvesting.

3.3 Hypothesis Testing

Maximum likelihood ratio test was used to assess the practical application of the Cobb-Douglas model, the presence of risk, and technical inefficiencies. The first hypothesis test result indicates that the Cobb-Douglas function adequately represents the data (Table 4). Table 4 rejected the second hypothesis, stating that production risk in input components does not explain output variability, at a significance level of 5%. Table 4 rejected the third hypothesis, which held that exogenous variables have no effect on technical inefficiency, at the 5% level of significance. The model should include both technical inefficiencies and production risk in input, as they both contributed to output variability. The estimated lambda in Table 5 is significantly different from zero (1.40364), indicating that inefficiency and production risk are important contributors to total output variability. The gamma (Table 5) parameter is estimated to be 0.663, which implies that 66.3% of the total variation in the maize output is due to technical inefficiency. The input parameters (Table 5) are measures of elasticities.

Table 4. Hypothesis test for model specification and statistical assumptions of stochastic frontier model with flexible risk properties

Null Hypotheses	Loglikelihood Of H_0	Loglikelihood Of H_a	Test Stat. (Λ)	Degree of Freedom	Critical Value $(\Lambda)^2$	Decision
$H_{0:}\beta_{jk} = 0$	426.9	428.2	2.60	1	2.71	Accept H_0
$H_{01}: \varphi_1 = \varphi_2 = \varphi_3 = \varphi_4 = 0$	422.1	437.0	29.8	4	8.76	Reject H_0
$H_{02}: \delta_1 = \delta_2 = \delta_3 == \delta_8 = 0.$	422.1	437.0	29.8	8	14.85	Reject H_0

Source: Field survey data, 2022. Note: Taken from Table 1 of [20] using 5% level of significance.

Table 5. Maximum Likelihood estimates of Cobb-Douglas mean output function

Variable	**Parameter**	**Estimates**	**Standard Error**	**P-value**
Constant	β_0	1.9770***	0.1140	0.000

Seed	β_1	0.1781***	0.3262	0.000
Fertilizer	β_2	0.6012 ***	0.0425	0.000
Agrochemicals	β_3	0.0311	0.0467	0.505
Labour	β_4	-0.0458*	0.2605	0.079
Variance parameters				
Sigma-square (μ)		0.06257		
Sigma-square (v)		0.44583		
Lambda ($\Lambda = \delta_\mu / \delta_v$)		1.40364		
Sigma^2 ($\delta^2 = \delta v^2 + \delta \mu^2$)		0.00590		
Gamma $\gamma = \Lambda^2/(1+\Lambda^2)$		0.66332		

Source: Field survey data, 2022: Note * and *** correspond with 10% and 1% level of significance Respectively

3.4 Elasticity of Production and Returns to Scale

Table 6 presents estimate of output elasticity with respect to production input. The parameters of the stochastic frontier model showed that all the output elasticity is positive except labour. The positive sign implies that as the variable input increased, output increased, and vice versa. The output elasticity for seed, fertilizer, agrochemicals, and labour are 0.1781, 0.6012, 0.0311, and -0.0458, respectively. This means that a one percent increase in the quantity of seed used per hectare, holding all other factors constant, will result in an output increase of 0.1781 percent. Similarly, a percentage increase in fertilizer employed per hectare will increase yield by 0.6012 percent. Also, a percentage increase in agrochemicals utilized will increase yield by 0.0311. Table 6 further shows that a percentage increase in labour used per hectare, holding all other factors constant, will decrease output by 0.0458 percent. The estimated return-to-scale value of 0.7646 indicates that a one percent increase in all inputs will result in a 0.7646 percent increase in maize output. The rate of return to scale also shows that the input allocation was in stage II of the production function. The result agrees with the findings of [21] and [22].

Table 6. Elasticity of production and returns to scale

Variables	Elasticities
Seed	0.1781
Fertilizer	0.6012
Agrochemicals	0.0311
Labour	-0.0458
Return to Scale (RTS)	0.7646

Source: Field survey data, 2022

3.5 Production Risk

Production risk in inputs is significant in the production process. The result (Table 7) of the study shows that fertilizer and seed are significantly risk-decreasing inputs in the study area, while labour and agrochemicals were risk-increasing inputs, though not significant. The result implies that effective and proper management of fertilizer and seed will reduce output variability and stabilize yield with the present technology. The estimate of fertilizer as risk-decreasing input agrees with [15]. Similarly, the estimate of seed as a risk-decreasing input aligns with the findings reported by [14]. Depending on the empirical data under analysis, production inputs can either increase or decrease risk [23].

Table 7. Maximum likelihood estimates of the linear production risk function

Variables	Parameters	Estimates	Standard error	P-value
Constant	φ_0	7.04582**	3.5603	0.048
Seed	φ_1	-2.2832*	1.3761	0.097
Fertilizer	φ_2	-3.0864**	1.3574	0.023
Agrochemicals	φ_3	1.04640	0.7883	0.184
Labour	φ_4	1.44028	1.3738	0.294

Field survey data, 2022. Note: * and ** denotes 10% and 5% significance levels

3.6 Determinants of Technical Inefficiency

The inefficiency parameters were specified as age, household size, education level, farming experience, extension contact, land cultivation technique, planting technique, and harvesting technique. Five out of eight variables used in the model have a priori expected signs, and four of the variables were statistically significant at the 10%, 5% and 1% probability levels. A negative coefficient indicates that the variable increases efficiency (reduces inefficiency) in the maize production and vice versa.

Table 8: Maximum likelihood estimates for parameters of inefficiency effects Cobb-Douglas stochastic production model.

Variable	Parameter	Coefficient	Std error	z-value
Age	δ_1	-0.00149**	0.00070	0.034
Household size	δ_2	0.01030	0.07870	0.896
Education level	δ_3	-0.08196**	0.04065	0.044
Farming experience	δ_4	-0.03460	0.03613	0.338
Extension contacts	δ_5	-1.47242***	0.44837	0.001
Land cultivation technique	δ_6	-0.05372*	0.03148	0.088
Planting technique	δ_7	0.22135	0.34858	0.525
Harvesting technique	δ_8	0.19512	0.34134	0.568

Source: Field survey data, 2022. **Note:** *, **, *** denote significance at 10%, 5%, and 1% Respectively

Table 8 demonstrates that age estimates significantly reduce the technical inefficiency of maize farmers at the 5% probability level. This could potentially be attributed to the dominance of young, energetic farmers in the study area. The results align with the findings presented in [22]. The extent of the inefficiency effects could vary greatly by the farmer's age [23]. It's likely that older farmers are more conservative and traditional, which would make them less willing to consider using new techniques and ultimately lead to higher inefficiency. But younger farmers might be energetic, risk-takers, and willing to consider using new technology, which could lead to higher efficiency. Depending on the empirical data under examination, the effect of age on technical efficiency varies [23]. The coefficient of education in Table 8 was negative and statistically significant at the 5% probability level. This implies that the estimated level of education is significantly reducing the technical inefficiencies of maize farmers in the study area. Higher education helps farmers become more knowledgeable, increases their technical efficiency, and fortifies their managerial abilities—all of which led to higher yields. The outcome is consistent with [24] and [15].

The estimate of extension contact in Table 8 shows that the variable has a negative relationship with technical inefficiency and is statistically significant at the 1% probability level. This implies that extension visits are a significant factor influencing the technical efficiency of maize farmers in the study area. By implication, extension contact will give maize farmers in the study area the opportunity to utilize new technology that could improve their skills and technical know-how, thereby increasing their productivity. [21] and [15] reported similar results in their analyses of technical efficiency among small-scale irrigated crop farmers in Taraba and Gombe States, Nigeria, and in their study of technical efficiency and production risk of rice farms under the Anchor Borrowers Programme in Kebbi State, Nigeria, respectively. Table 8 shows that land cultivation techniques have a negative effect on technical inefficiency and are statistically significant at the 10% probability level. The results suggest that the majority of maize farmers in the study area are reducing their technical inefficiency through tilling the land with tractors. This is because the harrow allows deep tillage in the soil, which could improve soil aeration and, consequently, increase yield. The result agrees with [15].

3.7 Technical Efficiency Estimates

Table 9 shows the distribution of farmers' technical efficiency indices that were obtained by analyzing the stochastic production function. The farmers in the research area were likely producing less than the frontier production, as shown by the technical efficiency of the sampled farmers being less than 1.00. Different levels of technical efficiency were noted in the farms that were sampled. Technical efficiency for the top farm was 0.97 (97%), and for the bottom farm it was 0.34 (34%). Accordingly, the farmer using the worst practices is 66% less productive than the farmer using the best practices. A specific mix of production inputs might yield around 75% of optimal output for maize farmers in the research area, according to the mean technical efficiency of 0.75 (75%) that was observed. This suggests that by implementing the technology of the best-practice Decision-Making Units (DMUs), farmers in the study area might potentially increase their technical efficiency by approximately 25% in the short term. In their various study areas, [25], [15], [14], and [21] each reported a similar outcome.

Table 9: Technical efficiency distribution of maize farmers in the study area

Efficiency scores	**Frequency**	**Percentage**
>0.90<1	30	10.03
>0.80≤0.90	55	18.40
>0.70≤0.80	88	29.43
>0.60≤0.70	34	11.37
>0.50≤0.60	36	12.04
>0.40≤0.50	34	11.37
>0.30≤0.40	22	7.36
Total	**299**	**100**
Mean	0.75966	
Minimum	0.34210	
Maximum	0.97390	

Source: Field survey data, 2022

4.0 CONCLUSION AND RECOMMENDATIONS

This study has estimated a stochastic frontier model with flexible risk properties. The study concludes that input factors determined maize output as well as production risk. On average, maize production in the study area has been technically efficient but below the frontier level. It's possible for estimates of technical efficiency to be wrong if the production technology is modeled without the flexible risk component and the risk-neutral inputs are used. The study suggests that policymakers should encourage the implementation of best farm practices and incorporate production risk into technical efficiency analyses when inputs are not risk-neutral. The study relies solely on cross-sectional data; therefore, future research should incorporate time series data to observe the annual fluctuations in agricultural outputs, inputs, and their prices. Lastly, the study did not include input factors like soil fertility, temperature, relative humidity, and prolonged drought; therefore, there is a need to include these factors in future studies.

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