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Factors Influencing Technical Efficiency of Maize Production Among Large-Scale Farmers in Tanzania

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KEYWORDS

Technical efficiency of maize production among Large-scale farmers in Tanzania

ABSTRACT

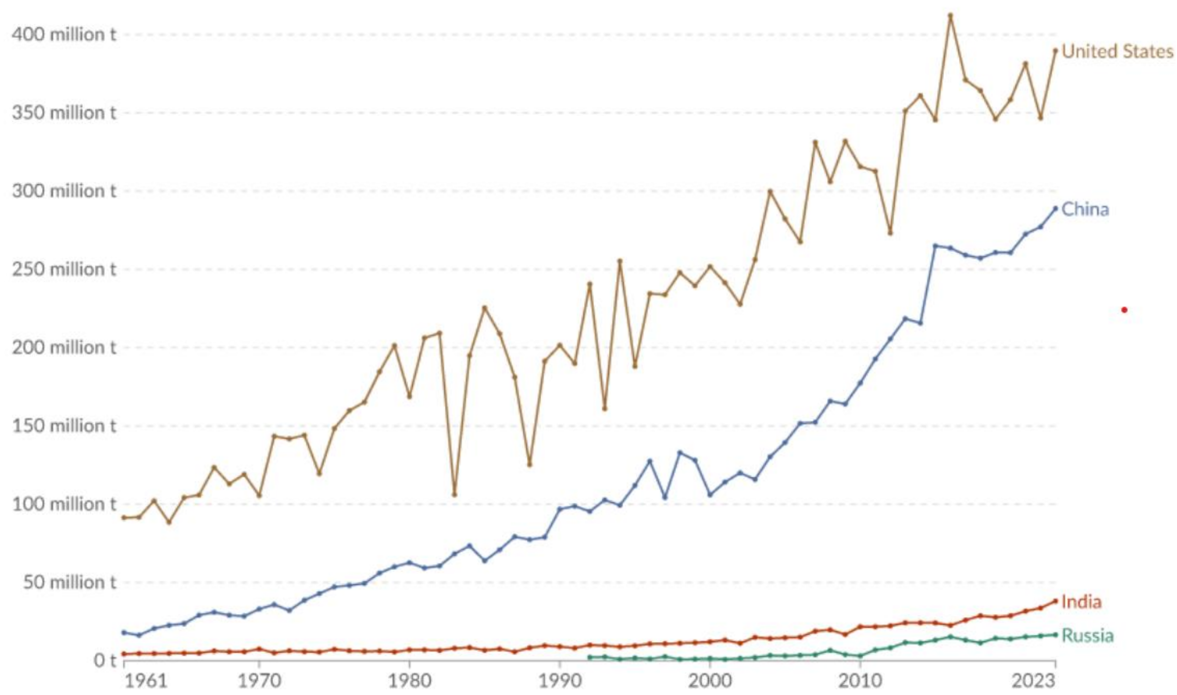
This study analyzed the factors influencing the technical efficiency of maize production among large-scale farms in Tanzania, using data from the 2019/2020 National Sample Census of Agriculture. Analytical methods included correlation analysis, multiple linear regression, and the stochastic frontier production function. Correlation results showed strong positive relationships between maize output and the costs of fertilizers (r=0.92), improved seeds (r=0.93), and modern machinery (r=0.89), while weaker correlations were observed with yield, agrochemical costs, and labor inputs. Regression analysis indicated that increased investment in improved seeds (1% increase leading to 63.1% rise in output), fertilizers (43.6%), and modern machinery (30.6%) significantly boosts maize production. Conversely, agrochemical costs and labor inputs negatively affected output, suggesting inefficiencies and possible misuse. Stochastic frontier results revealed that 48.69% of farmers operate with low technical efficiency (scores between 0.1 and 0.3), largely due to inadequate farm management, poor input access, and limited technical support. Around 43.46% fell into a moderate efficiency range (0.4–0.6), while only 7.85% were highly efficient (0.7–0.9). The study concluded that most large-scale maize farmers are not reaching optimal efficiency levels. It recommended enhancing access to fertilizers, improved seeds, and modern machinery through supportive policies and capacity building

1.0 Introduction

1.1 Background

Maize (Zea mays), also known as corn, is a major global staple used for both human consumption and animal feed. In 2022, the U.S. led global maize production with 349 million metric tons, followed by China with 277 million and Brazil with 109 million metric tons (FAO, 2023). From 1961 to 2023, maize production in the U.S. steadily increased from 100 million to over 400 million tons, despite occasional fluctuations. China started with about 20 million tons in 1961 and saw rapid growth from the late 1990s, reaching over 280 million tons by 2023. India's maize production rose slowly from below 5 million tons in 1961 to around 40 million in 2023, possibly due to challenges like small-scale farming, climate change, and limited infrastructure. Russia had minimal maize production until the 1990s but began a moderate increase around 2000, reaching 15–20 million tons by 2023.

Figure 1: Trend of maize production of USA, China, India and Russia from 1961 to 2023



Source: (FAOSTAT, 2025)

The Americas lead global maize production with 50% of the total output, driven by advanced technology and large-scale farming, followed by Asia (32%), Europe (11%), and Africa (8%). In

Africa, South Africa, Nigeria, Ethiopia, Egypt, and Tanzania are the top producers, with Tanzania ranking fifth, contributing 7% of the continent's maize output. Despite maize being grown nationwide, Tanzanian production mainly from small-scale farmers suffers from low technical efficiency due to poor farming practices, limited mechanization, and inadequate access to modern inputs and extension services.

While large-scale farmers have more resources, they often underutilize them, resulting in suboptimal yields compared to global standards. The government has launched initiatives like ASDP II and adopted policies emphasizing modern farming and research into drought-resistant varieties, yet challenges such as regional disparities, post-harvest losses, and limited financial and technical support persist. To enhance productivity, targeted interventions must address access to technology, input quality, market linkages, infrastructure, and farmer training across regions

1.2 Statement of the Problem

Despite efforts to boost maize yield through large-scale farming, productivity in Tanzania remains low, averaging between 1.5 and 2 tons per hectare well below the potential 4 to 6 tons per hectare. This yield gap calls for effective strategies aligned with SDG 2 to improve maize production efficiency. However, recent studies focusing on large-scale farmers have not fully explored the factors affecting technical efficiency and spatial variability in maize production (Digest Tanzania, 2024), (Lelei, Sultan, & Kuboja, 2025) and (Lema & Temu, 2023). This study addresses this gap by analyzing the technical efficiency of maize production among large-scale farmers using data from the 2019/20 National Sample Census of Agriculture NBS (2021).

1.3 Objectives of the Study

1.3.1 Main objective

The study aimed at analyzing factors influencing technical efficiency of maize production across of large-scale farmers in Tanzania.

1.3.2 Specific objectives

The specific objectives of this study were:

i. To analyze spatial variation of maize production through large scale farming

ii. To determine factors influencing output of maize produced through large scale farming
iii. To analyze technical efficiency levels of maize produced through large scale farming
iv. To determine factors influencing technical efficiency of maize produced through large scale farming

1.4 Research Questions

The research questions for this study are:

i. What is the spatial distribution of maize production by large-scale?
ii. In what ways do technical efficiency levels of maize production differ across regions with large-scale farming?
iii. What are the key factors influencing maize output among large-scale farmers?
iv. What socio-economic factors contribute to variations in maize productivity among large-scale farmers?

2.0 Review of Theoretical and Empirical Literature

2.1 Production Theory

Production theory is an economic framework that explores the connection between inputs—such as labor, capital, and raw materials—and the resulting output, emphasizing the efficient combination of these inputs to produce goods and services (Ricardo, 1817). It describes how producers optimize the use of resources to either maximize output or reduce costs. Typically, the theory assumes a linear relationship between inputs and output, often represented by the Cobb-Douglas production function (Cobb & Douglas, 1928), where output (Y) is influenced by labor (L), capital (K), and total factor productivity (A). Labor plays a critical role in agricultural tasks like planning and harvesting, with greater labor input leading to improved efficiency and higher yields (Grabowski, 2016; Torres, 2008). Capital, including machinery and technology, contributes to production efficiency by mechanizing operations and enhancing infrastructure (Belgraver & Verwaal, 2018). Various studies have utilized the Cobb-Douglas function to examine how different production factors impact output (Hayami & Ruttan, 1985; Friedrich et al., 2009; Miller

& Upton, 1985; Awerbuch & Berger, 2003; Barro & Sala-i-Martin, 1995). This study applies production theory to evaluate how inputs affect maize production.

2.2 Empirical Literature Review

2.2.1 Factor affecting maize production among large scale farms

Several studies have examined factors influencing maize production in different regions. Andisiwe and Wang (2020) found that fertilizer, labor, and herbicide use significantly increased maize production in South Africa, recommending subsidized inputs and improved extension services. Njogu (2019) reported that land size, machinery use, and chemicals positively affected maize production among small-scale farmers in Kenya, while extension services had a negative effect, and seed and fertilizer application showed no influence. Mohammed (2021) identified income from non-farm activities, input costs, and farm size as key factors affecting maize production in Ethiopia, urging policymakers to promote maize cultivation and supply improved seeds and fertilizers. Maguja and Mlilile (2023) analyzed Tanzania's maize production over 61 years and found cultivated area positively and significantly related to output, while fertilizer price and expected maize price negatively influenced production; they recommended policies supporting intensive agriculture, subsidies, and irrigation. Lastly, Utouh (2024) found farm size, irrigation access, and improved seeds significantly impacted maize production in Tanzania, emphasizing the need to improve smallholder farmers' access to irrigation and modern inputs

2.2.2 Effect of social-economic factors on maize production among large scale farms

Different studies have explored the influence of socio-economic factors on maize production. Msigwa (2018) found that household size, farm size, pesticide costs, and access to credit significantly affected maize production in Tanzania, with mixed farming systems better adapting to rainfall variability. The study recommended environmental education, expansion of mixed farming, and formation of farmer cooperatives for affordable loans. Mogeni (2019) identified land size, seed quantity, fertilizer and pesticide use, and credit access as positive influences on maize productivity in Kenya, alongside factors like farming experience, extension services, and education level; recommendations included improving input availability, tackling corruption, and revising land tenure systems. Aakash (2019) reported that geographical location, household size, cultivated area, sex, and education influenced maize yields in Tanzania, calling for further research on income, credit access, labor, fertilizer quality, and market access. Adeola and Yusuf (2023) studied maize farmers in Nigeria and found age and education significantly impacted scale efficiency, with high input costs being a major challenge; they recommended farmer education and input subsidies. Zhexi and Jiashuo (2022) showed that climatic factors such as temperature and precipitation positively affected maize output in China, along with labor and capital inputs; they stressed the importance of climate prediction, farmer training, and irrigation projects to support sustainable production

3.0 Methodology

3.1 Study Area

The study was conducted in Tanzania, a country in Eastern Africa bordered by several nations and the Indian Ocean, with agriculture being a key sector for food security, employment, and economic growth. Maize is one of Tanzania's major crops and a vital income source for both smallholder and large-scale farmers. Despite its importance, maize production faces significant challenges related to technical inefficiency and low productivity. Tanzania's diverse agroecological zones make it an ideal location to assess environmental and technological impacts on maize production, offering valuable insights for policy development to enhance agricultural sustainability. (Tanzania Ministry of agriculture, 2015)

3.2 Research Design

This study used a quantitative research design to analyze factors affecting technical efficiency in large-scale maize production in Tanzania (Utouh, 2024).

3.3 Sampling and Population

The National Sample Census of Agriculture (NSCA) gathered data on both small-scale farmers (households) and large-scale farms. While data for small-scale farmers was collected using sampling techniques, information on large-scale farms was obtained through complete enumeration. Since this study focuses on large-scale maize farmers, no sampling method was applied; instead, all relevant farms were included. Out of 1,093 large-scale farms recorded in

Tanzania, 306 were reported to have cultivated maize during the 2019/20 agricultural year (NBS, 2021), making up the total number of large-scale farms analyzed in this research.

3.4 Data Source

The study used secondary data obtained from National Sample Census of Agriculture 2019/20 agriculture year Report. (National Bureau of Statistics, 2020). This survey provides credible data that answered objectives regarding factors affecting technical efficiency of maize by large-scale farms.

3.5 Data Analysis

3.5.1 Descriptive statistics

Descriptive analysis involved measures of central tendencies and dispersion as well. The study used descriptive statistics such as means, percentages, standard deviation and frequency tables and charts. statistics used to describe the central tendencies and measures of dispassion of data such mean, maximum, minimum and standard deviation.

3.5.2 Correlation

Correlation analysis used to assess the extent or strength of the relationship between variables. Based on this study, Pearson correlation was used to see how the amount of maize harvested is related to other influencing factors, also how each factor relating to another factor.

. The correlation question is given by $r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2} \cdot \sqrt{\sum(y_i - \bar{y})^2}}$ or $r = \frac{Cov(X,Y)}{\sigma_X \cdot \sigma_Y}$

r = Peason correlation coefficient

$x_{i,} y_i$ = individual data points in variables X and Y,

$\bar{x}, \bar{y}$ = means of variables X and Y

$Cov(X,Y)$ - covariance between X and Y

$\sigma_X \cdot \sigma_Y$ - standard deviations of X and Y

The value of r ranges from -1 to +1

If r = 1, then perfect positive correlation, this indicating that once a unit of one variable increase also other related variable increase, if r = -1, then perfect negative correlation, this indicating that once a unit of one variable increase, other related variable decrease also if r = 0, then no linear correlation, there is no linear relationship between variables

3.5.3 Regression analysis

Regression is a broad statistical technique used to model and analyze the relationship between a dependent variable (Y) and one or more independent variables (X). Th Studies of Aakash (2019); Mohammed (2021); Temotf and Ethel (2023); and Utoch (2024) applied to analyse the association between independent and dependent variables. A regression model with a single independent variable is referred to as a Linear Regression model, while one with multiple independent variables is known as a Multiple Regression model.

The regression model was specified as:

$Yi=\beta 0 + \beta iXi+ \epsilon i$ ……………………………………………………………………………......**(2.1)**

Where:

Yi is the variable of interest (response/dependent)

β0 is the Intercept (constant)

βi is the Coefficients of *Xi* or slope of associated with each predicted variable

Xi is the vector of the predictor variable

ϵi is the Error term,

Additionally, the objective of regression analysis in this study was to estimate the coefficients β_0, β_1, ..., β_k, and suitable methods is Ordinary Least Squares (OLS), since it minimizes the sum of the squared differences between the actual observed values of the dependent variable (Y) and the values predicted by the model

3.7.4 The stochastic frontier production function.

The Stochastic Frontier Production Function (SFPF) is a model used to assess production efficiency by separating output variation into two components: random error and technical inefficiency (Aigner, 1977). The random error term (Vi) captures unpredictable factors like weather, pests, and measurement errors, assumed to follow a normal distribution with a mean of zero. The inefficiency term (Ui) represents the degree to which a farm operates below its potential, modeled with a truncated normal distribution, where the mean is influenced by farm-specific variables (Zi) and associated parameters (δ).

The production output for a farm is a function of various inputs such as land, labor (permanent and temporary), seed types (local and improved), machinery value, credit, and other inputs like agrochemicals. The model distinguishes between actual output (Yi) and **potential (frontier) output (Yi)**, where technical efficiency (TE) is the ratio of the two. If Ui = 0, the farm is fully efficient; if Ui > 0, it is technically inefficient (Dey et al., 2000).

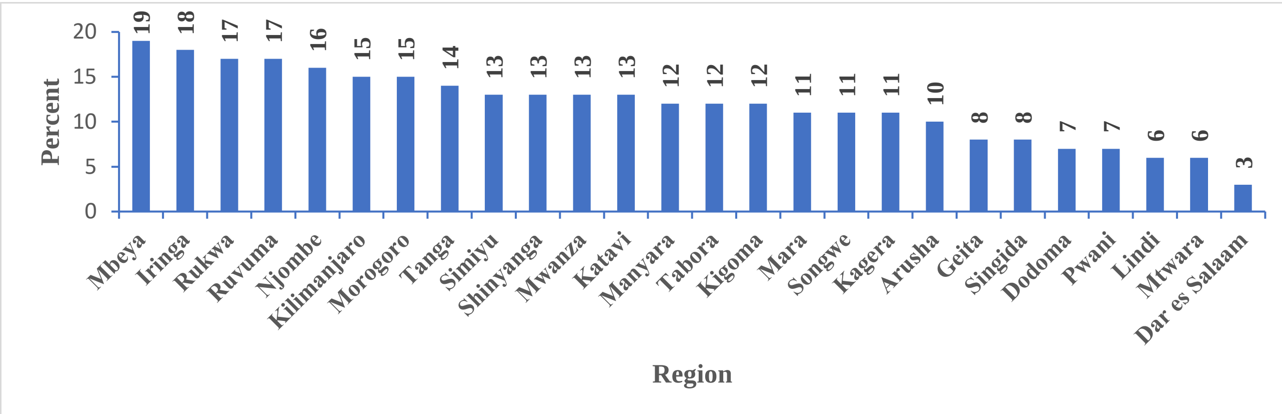
In the second stage of analysis, sources of inefficiency are explored using variables such as use of improved seeds, gender of workers, access to credit, land ownership, environmental conservation practices, irrigation, and extension services. Each variable's effect on inefficiency is analyzed through a model where parameters (δ_i) indicate the strength and direction of influence

4.0 RESULTS AND DISCUSSION

3.1 Descriptive Statistics of the Studied Variables

The results figure 2 show the frequency distribution of large-scale farms in Tanzania mainland by region, The total number of observations were 306 farms, the results show that, the highest number of large-scale farms reported in Mbeya (19 farms equivalent to 6.2 percent), followed by Iringa (18 farms equivalent to 5.9 percent), Rukwa and Ruvuma regions with 17 farms equivalents to 5.6 percent each. Also figure 2 show that, lowest number of farms reported in Dar es salaam with only 3 farms equivalents to 1.0 percent, followed by Mtwara with 5 farms equivalent to 1.6 percent and Lindi 6 farms equivalent to 2.0 percent. In general 73 percent of all regions have farm greater than 9 and the 27 percent have less than 9 farms

Figure 2: Frequency distribution of large-scale farms by region



Source: Author's compilation (2025)

Also, the results in Table 1 the study found that only 44.1% of large-scale maize farms used irrigation, reflecting a high dependence on rainfall and exposure to climate risks—similar to Grassin et al. (2011), who reported irrigation rates below 47% for cereal crops. Male workers made up 64.99% of the agricultural labor force, indicating a persistent gender gap, supported by Sawe (2018), and pointing to the need for gender-inclusive agricultural policies. Sustainable farming practices were adopted by 59.2% of farms, while 40.8% did not, suggesting the need for policy incentives to promote environmental conservation. Private ownership dominated at 80.7%, aligning with national trends and indicating the importance of supporting private farm investments. Financially, 91.5% of farms relied on loans, with only 8.5% operating without borrowing, reflecting limited internal capital. This trend parallels findings by Hoppe et al. (2021), who observed that credit dependence accounts for up to 95% of U.S. farm debt. Overall, key areas for policy focus include irrigation, gender equity, sustainability, ownership support, and farm financing.

Table 1: Frequency and Percentage Distribution of Categorical Variables

Variables	Categories	Frequency	Percent
	Irrigated	135	44.1
	Not irrigated	171	55.9
Farms Irrigated	**Total**	**306**	**100**

	Male	2445	64.99
	Female	1317	35.01
Sex	**Total**	**3762**	**100**
	Yes	181	59.2
	No	125	40.8
Environment Conservation	**Total**	**306**	**100**
	Government	59	19.3
	Private	247	80.7
Farm Ownership	**Total**	**306**	**100**
Number of Farms borrowed	Borrowed	280	91.5
	Not Borrowed	26	8.5
	Total	**306**	**100**

Source: Author's compilation (2025)

The results in Table 2 show that large-scale maize farms had an average harvest of 504 tons, with a range from 30 to 18,066 tons. The average maize cultivation area was 303 hectares, ranging from 20 to 8,047 hectares. Average yield was 1.7 tons per hectare, with yields ranging from 1.1 to 2.2 tons/ha, aligning with NSCA (2007/08) estimates of 1.7–2.8 tons/ha. On average, farms spent 10.7 million TZS on fertilizer, 42.9 million TZS on modern machinery, and 24.1 million TZS on agrochemicals. The mean cost of improved seeds was about 5.66 million TZS, with a wide variation between 100,000 and 115 million TZS. The average number of employees per farm was 73, with a maximum of 5,136; permanent employees averaged 16 and temporary 57. For irrigated farms, the average maize harvest was 741.7 tons, while unirrigated farms harvested an average of 6,705.7 tons. Farms using both irrigation types had a mean harvest of 7,446.6 tons. Mean yield from irrigated areas was 2.91 tons/ha, unirrigated areas had 2.98 tons/ha, and the overall yield averaged 2.89 tons/ha, indicating relatively similar performance across irrigation types

Table 2 Summary statistics for the quantitative data variables

Variable	Unity	Mean	Std. dev.	Min	Max
Quantity Harvest	Tons	504	1,485	30	18,066
Planted Area	Ha	303	723	20	8,047
Yield	Ton/Ha	1.7	2.1	1.1	2.2
Fertilizers cost	TZS	10,700,000	21,700,000	103,800	296,000,000
Modern machines cost	TZS	42,900,000	32,800,000	17,800,000	532,000,000
Agrochemicals cost	TZS	24,100,000	28,000,000	25,000	101,000,000
Improved seeds cost	TZS	5,656,930	10,000,000	100,000	115,000,000
Total employees	Number	73	324	5	5,136
Permanent employees	Number	16	62	1	954
Temporary employees	Number	57	309	4	1,130

Source: Author's compilation (2025)

3.2 Correlation Analysis

The results from Table 4.3 reveal strong positive correlations between the quantity of maize harvested and key input costs, based on 306 observations. The strongest correlation was found between harvest quantity and improved seed costs (r = 0.93), followed by fertilizer (r = 0.91) and modern machinery (r = 0.89), suggesting that increased investment in these inputs significantly boosts total output. These findings align with previous studies, such as those by Mdoda et al. (2025), Ragasa et al. (2025), and Majebele et al. (2025), which highlight the positive impact of improved inputs and mechanization on maize yield. Conversely, weak correlations were observed between harvest quantity and yield per hectare (r = 0.22), labor inputs (r = 0.07–0.12), and agrochemical costs (r = 0.07), indicating that productivity gains are more related to expanded cultivated areas and input intensity rather than efficiency. Moreover, strong inter-correlations among input costs such as improved seeds vs. fertilizer (r = 0.95) and fertilizer vs. machinery (r = 0.93) show that these inputs are closely linked and often used together to drive higher production. This supports findings from Kirui & von Braun (2019) and Roman Hadi & Wuepper (2024), who observed that mechanization tends to increase both land use and input application. Overall, the findings suggest that maize production is heavily driven by capital-intensive inputs, while labor plays a limited role, likely due to mechanization. However, the low correlation with yield per hectare points to inefficiencies in input use and a reliance on land expansion rather than improved productivity

Table 3: Pearson Correlation analysis

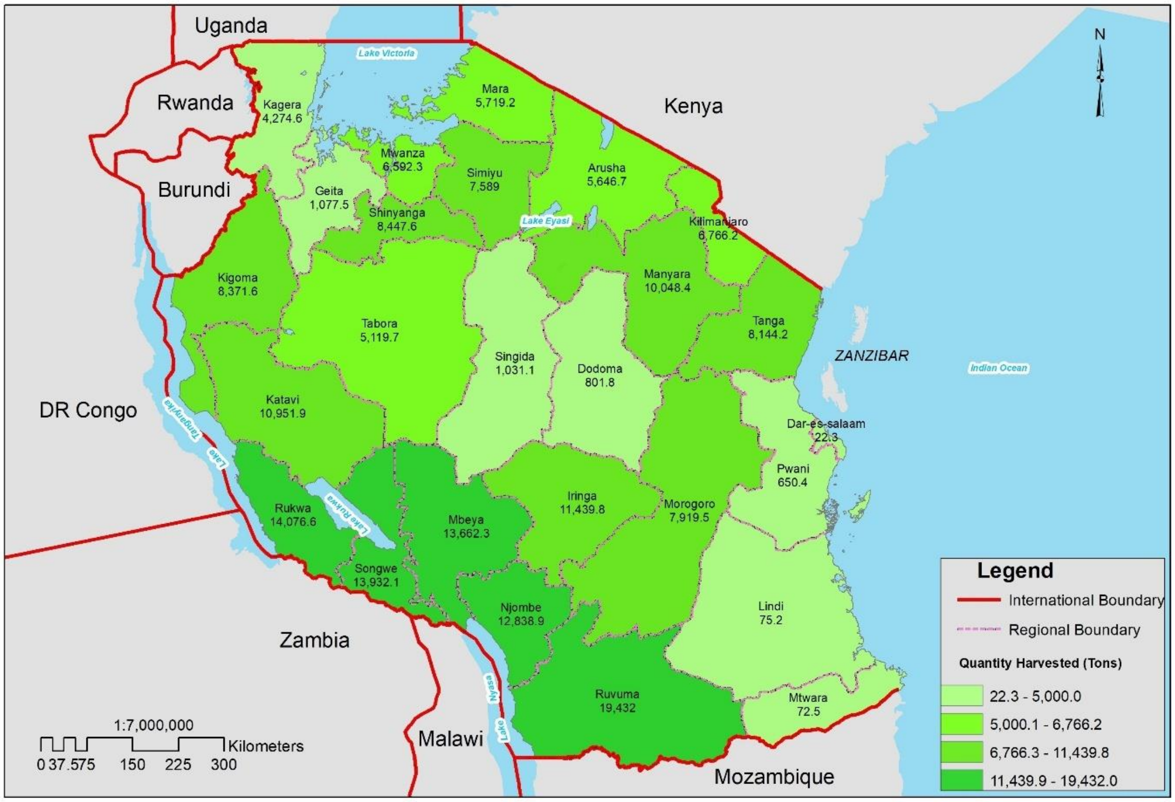
	QMP	YLD	VFU	VAGC	VMM	VIS	TNE	NPE	NTE
QMP	**1**								
YLD	0.22	**1**							
VFU	0.92	0.07	**1**						
VAGC	0.07	0.13	0.06	**1**					
VMM	0.89	0.03	0.93	0.08	**1**				
VIS	0.93	0.09	0.95	0.05	0.86	**1**			
TNE	0.07	0.01	0.10	-0.08	0.10	0.08	**1**		
NPE	0.05	0.01	0.08	-0.06	0.08	0.06	0.98	**1**	
NTE	0.12	0.01	0.13	-0.09	0.13	0.12	0.33	0.14	**1**

Source: Author’s compilation (2025)

3.3 Determining the Spatial Variation of Maize Production by large-scale in Tanzania

Figure 3 shows that maize harvest quantities vary by region, with the Southern Highland including Rukwa, Mbeya, Songwe, Ruvuma, Njombe, and Iringa producing the highest amounts, ranging from 11,439.9 to 19,432 tons. Regions like Morogoro, Katavi, Tanga, Manyara, Simiyu, Shinyanga, and Kigoma had moderate production, between 6,766.3 and 11,439.8 tons. The lowest production levels were seen in Mtwara, Lindi, Pwani, Dar es Salaam, Dodoma, Geita, and Singida, with outputs ranging from 22.3 to 5,000 tons. A similar study by Mundia et al. (2021) supported these findings, using GIS and spatial analysis to map maize productivity across Tanzania. That study also identified the Northern and Southern Highlands as top producers, while coastal and western regions showed lower productivity. The spatial distribution reflects differences in agro-ecological conditions, infrastructure, and farming practices. The use of geographic tools, like GPS and thematic maps, provided clearer insight into regional productivity patterns. These results highlight the importance of location-specific interventions to boost maize yields in underperforming areas. Overall, regional disparities suggest that agro-ecological potential and resource access significantly influence maize production across Tanzania.

Figure 3: Spatial Variation of Maize Production by Large-scale in Tanzania



Source: Author’s compilation (2025)

3.4 Factors affecting output of maize produced by large-scale farmers

The results presented in table 4 indicate that the model is highly significant in estimating the factors influencing maize production. The value of the coefficient of multiple determination (R^2) is 0.9294, meaning that 92.94% of the total variation in the dependent variable (output) is explained by the independent variables included in the model. Therefore, the model provides a good fit for the data.

Table 4 OLS estimates for parameters of the Cobb-Douglas production function for Maize

Lnoutput	**Parameters**	**Coefficient**	**Std. err.**	**t**
Lnfertilizerscost	β1	0.436***	0.045	9.65
lnmodernmachinescost	β2	0.306***	0.102	3
lnagrochemicalscost	β3	-0.023*	0.013	-1.8
Lnimproved seeds cost	β4	0.631***	0.048	13.12
Lnlabour	β5	-0.035**	0.015	-2.26
Constant	β0	-15.611***	1.570	-9.94

Note: Significance levels of 1%, 5%, and 10% are indicated by ***, **, and * respectively.

Source: Author's compilation (2025)

R^2 = 0.9294

Adjusted R^2= 0.9282

The regression results indicate that input costs for improved seeds, fertilizer, and modern machinery have a significant and positive impact on maize output. Specifically, a 1% increase in fertilizer cost leads to a 43.6% rise in output, reflecting efficient fertilizer use, as supported by studies like Ragasa and Chapoto (2017). Improved seeds show the strongest effect, where a 1% cost increase results in a 63.1% rise in output, while modern machinery contributes a 30.6% increase. In contrast, agrochemical costs negatively affect output a 1% increase leads to a 2.3% decline possibly due to overuse or poor application practices. Labor input also shows a negative effect, with a 1% increase reducing output by 3.5%, suggesting inefficiency in labor utilization. Overall, the Cobb-Douglas production function reveals that seed and fertilizer investments are the most productive, while labor and agrochemicals reduce efficiency. The estimated return to scale is 1.315, indicating increasing returns, doubling all inputs would more than double the output emphasizing the importance of efficient input management to enhance maize productivity

3.5 Analysis of technical efficiency levels of maize produced across regions with large-scale farmers

The results in Table 4.5 present maximum likelihood (ML) estimates from a Cobb-Douglas stochastic frontier production function for maize, showing the model is highly significant in identifying factors influencing maize production. Fertilizer cost, modern machinery cost, and improved seed cost were all positive and statistically significant at the 1% level, indicating these inputs are elastic meaning a 1% increase in each lead to a corresponding 1% increase in output. Among them, improved seeds had the greatest impact, with an elasticity of 0.631, followed by fertilizers (0.436) and modern machinery (0.306). This highlights the critical role of these inputs in boosting maize production. Conversely, labor and agrochemical costs were negatively associated with output, with elasticities of −1.000 and −1.000 respectively, and were significant at the 5% and 10% levels, suggesting inefficiencies or mismanagement in their use. These findings are supported by Biswas et al. (2022), who found similar elasticity values in a Cobb-Douglas model for maize in Bangladesh—confirming the strong positive effects of fertilizer, improved seeds, and machinery, and negative impacts from labor and agrochemicals. Additionally, the estimate for gamma (γ) was 0.002 (0.2%), implying that only a small portion of the variation in maize output is due to technical inefficiency, with the vast majority (99.8%) explained by random shocks. However, the large standard error (0.156) indicates that γ is not statistically significant. Similar results were reported by Abdulai & Tietje (2007) and Deribe et al. (2022), who found that most output variation in stochastic frontier models stems from random factors rather than inefficiency

Table 5: ML estimates for the parameters of the Cobb-Douglas stochastic frontier production function of Maize

Lnoutput	Parameters	Coefficient	Std. error.	z

Constant	β0	-15.606***	1.575	-9.91
lnfertilizerscost	β1	0.436***	0.045	9.74
lnmodernmachinescost	β2	0.306***	0.101	3.03
lnagrochemicalscost	β3	-0.023*	0.013	-1.81
lnimprovedseedscost	β4	0.631***	0.048	13.25
Lnlabour	β5	-0.035**	0.015	-2.28
Constant	β0	-15.606***	1.575	-9.91
γ		0.002	0.156	
σ^2		0.198	0.034	
Log Likelihood		-185.96477		

Note: Significance levels of 1%, 5%, and 10% are indicated by ***, **, and * respectively

Source: Author’s compilation (2025)

3. 6. Effect of socio-economic factors on maize production among large-scale farmers

Table 4.6 presents the maximum likelihood estimates identifying the socio-economic determinants of technical inefficiency among maize producers. In this inefficiency effects model, negative coefficients indicate increased efficiency, while positive ones suggest greater inefficiency. Farm size shows a positive but statistically insignificant coefficient (0.007), implying a weak link between larger landholdings and efficiency, consistent with Alene and Hassan (2003), who found mixed results depending on context. Farm ownership has a significant positive effect (0.049), suggesting that private landowners are more efficient due to stronger investment incentives—a finding aligned with Ogunwusi and Oladele (2024). Environmental conservation practices yield a negative but insignificant coefficient (−0.007), indicating no clear efficiency impact, which is consistent with Dang (2017), who noted similar results. The constant term (0.322), significant at the 1% level, suggests a baseline technical efficiency of 32.2%, highlighting the presence of unexplained inefficiencies, as also observed by Dang (2017) and Esham (2014)

Table 6: Maximum likelihood estimates (MLEs) of determinants of technical efficiency of Maize. Production

TE	Parameters	Coefficient	Std. err.	t
lnfarmsizeinha2	δ_1	0.007	0.006	1.13
Farm ownership (Private)	δ_2	0.049**	0.024	2.04
Environmental conservation (Dummy)	δ_3	-0.007	0.019	-0.35
Constant	δ_0	0.322***	0.033	9.63

Note: Significance levels of 1%, 5%, and 10% are indicated by ***, **, and * respectively.

Source: Author's compilation (2025)

3.7. Technical Efficiency Levels of Maize Production

A score of with 0, this is totally inefficiency and also if the score is 1.0 indicate perfect efficiency, when the score is close to 1.0 this indicating high efficiency. On the other hand, if the technical efficiency score is close to 0 this indicating low efficiency

Table 7: Frequency distribution of technical efficiencies of maize growers

Efficiency Level	Technical Efficiency	Frequency	Percent
Low Efficiency	0.1 - 0.3	149	48.69
Moderate Efficiency	0.4 - 0.6	133	43.46
Highly efficient	0.7 - 1.0	24	7.85
	Total	306	100
	Mean	102	
	Minimum	10%	
	Maximum	90.0%	

Source: Author's compilation (2025)

Table 4.7 illustrates the distribution of technical efficiency (TE) scores among 306 maize farmers, revealing substantial inefficiencies in production. The scores range from 0.1 to 0.9, indicating how closely farmers operate to the production frontier. Nearly half of the farmers (149 individuals or 48.69%) had TE scores between 0.1 and 0.3, suggesting that many operate at less than 40% of their potential, possibly due to factors such as poor farm management, lack of quality inputs, inadequate extension services, and limited technical know-how. Another 133 farmers (43.46%) fell within the moderate efficiency range of 0.4 to 0.6, showing some productive capacity but still considerable room for improvement. Only 24 farmers (7.85%) achieved high efficiency, with scores between 0.7 and 0.9, indicating proximity to optimal resource utilization. These findings align with earlier studies; for example, Masuku et al. (2021) found TE scores from 2% to 84% among 400 Zambian maize farmers, with 14% scoring below 30% and 14% above 70%. Similarly, Bempomaa and Acquah (2014) observed an average TE of 67% among 306 maize farmers in Ghana, implying a 33% efficiency gap. These comparisons reinforce the current study's conclusion that most farmers remain below the production frontier due to inefficiencies not entirely explained by observable variables.

4.0 CONCLUSION AND POLICY IMPLICATIONS

The study found significant spatial variation in maize production across Tanzania, with the Southern Highlands—notably Rukwa, Mbeya, Songwe, Ruvuma, Njombe, and Iringa—recording the highest outputs, while regions like Mtwara, Lindi, and Dar es Salaam had the lowest. Key factors positively affecting maize production included fertilizers, improved seeds, and modern machinery, all significant at the 1% level, whereas agrochemicals and labor negatively impacted output at 10% and 5% significance levels, respectively. Improved seeds had the strongest influence on output with a coefficient of 0.631, followed by fertilizers (0.436) and modern machines (0.306), confirming their role in increasing productivity and efficiency. Conversely, an increase in agrochemical uses and labor led to declines in efficiency, suggesting overuse or inefficiency in their application. The inefficiency analysis showed that technical inefficiency accounted for only 0.2% of output variation, while 99.8% was due to random shocks, indicating external factors play a larger role in production variability. Lastly, efficiency levels revealed that 48.69% of farmers operated at low efficiency, 43.46% at moderate, and only 7.85% at high efficiency, pointing to a need for better education, access to inputs, and extension services to improve productivity.

The study recommends that policymakers improve access, affordability, and distribution of key agricultural inputs—such as fertilizers, improved seeds, and modern machinery—through subsidies, better supply chains, and stronger extension services to boost maize productivity. It also calls for increased investment in large-scale farming, focusing on easing capital constraints and promoting efficient input use, while addressing the negative impacts of labor and agrochemical misuse through training, education, and technology adoption. Finally, to enhance overall technical efficiency—particularly among the nearly 49% of low-efficiency farmers—the study urges support for capacity-building, agricultural financing, and farmer cooperatives, with further research needed on infrastructure, market access, climate change, and post-pandemic impacts on maize production

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