Technical Efficiency of Smallholder Farmers in Tanzania: A Stochastic Frontier Approach

ABSTRACT

Aims: This study focused on determining the level of technical efficiency (TE) and its corresponding common factors across all crops grown by Tanzanian smallholder farmers. The motive of this study came from production theory and production efficiencyand the research was strongly attracted by the ongoing subsistence nature of the agriculture sector in the country that doesn’t fully meet the desired productivity

Method

ology: The study employed the cross-sectional National Sample Census of Agriculture 2019/2020 dataset while focusing on smallholder farmers operating in the long-rainy season by employing a single-step stochastic frontier model with an assumption of a Cobb-Douglas production function.

Results: The results of production on frontier show that land size (Ha), seeds (Kg), and fertilizers (Kg) are the main requirement for smallholder farmers to produce their maximum output. Based on the efficiency equation, improved seeds, inorganic fertilizers, and access to extension services decrease farmers' technical inefficiency while household age and membership in a cooperative organization increase farmers' technical inefficiency. Further, the average level of technical efficiency among smallholder farmers in Tanzania is 56.7% which allows farmers to increase their output level up to 43.2% with the same level of inputs.

Conclusion: As per the results, improved seeds and inorganic fertilizers are essential, however farmers organizations act as stumbling blocks. Thus, in this regard,Tanzanian farmers still have a room to improve and unlock their full potential, and so it is imperative for the government to take immediate measures to improve their technical efficiency such as introduction of more irrigation schemes, improved seed subsidies among others and farmers organizations should also be enhanced and streamlined to support farmers efficiency

Keywords: Production, efficiency, stochastic frontier, agriculture, crop yield

1. INTRODUCTION

Indeed, the agriculture sector has remained to be the most dominant in the economies of many developing countries (Akite et al., 2022). The agriculture sector in developing countries is dominated by smallholder farmers as a result production level and production efficiency are very low because they are faced with poverty which limits their accessibility and ability to adopt modern technology (Anang et al., 2016). According to Iticha, (2020), low productivity among smallholder farmers is associated with decreased food security and has aggravated the food insecurity problem by increasing the yield gap between the food demand and the supply available. Based on recent projections, it was assumed that by 2050, global agriculture production level in terms of value will grow by 60% however this projection is said to be limited due to limited arable land as a result, this achievement is ought to be reached by depending on one approach of increasing crop yields through better and optimal use of available agriculture inputs (Dijk et al., 2017).

Although there are inefficiencies in the agriculture sector but most developing countries, agriculture has for certain remained to be a dominant sector in the economy (Anang et al., 2016). According to Chongela, (2015), agriculture's annual average share of the national GDP in Tanzania from 1981 to 2010 was approximately 25.88%. Agriculture is made up of other small subsectors such as crop subsector, livestock, and fisheries. The crop subsector alone has been noted to be contributing an approximate 18.93% annual average share of the total GDP (Ibid). Further, according to the Tanzania National Five-Year Development Plan phase three (FYDP3) of the year 2021/2022 to 2025/2026, agriculture has contributed an average of 27.7% of the total GDP, 24.1% earning from export, and over 60% employment opportunities (URT, 2021). Further, this contribution indeed makes agriculture the second largest contributor to the economy after the service sector which contributes more than 40% to the national economy based on typical statistics (Chongela, 2015). Thus, this information act as an alarm that agriculture is a very important and delicate sector and should be taken seriously when it comes to maintaining production output and technical efficiency since agriculture is the main source of livelihood among the huge population of smallholder farmers who at most

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lives in rural areas (Miho, 2017). Following the notable contribution of the agriculture sector in developing countries including Tanzania to be specific, it is recommended that the best way of transforming agriculture performance and increasing food security is to increase productivity by enhancing efficiency in cereal production by adopting modern technology and formulating policies based on key factors that contribute to the improvement of technical efficiency in agriculture production which in one way or another will result to optimal utilization of the available scarce resources (Tiruneh & Geta, 2016).

This paper is derived from the undeniable significance of the agriculture sector in Tanzania as it focuses on the analysis of agriculture technical efficiency of smallholder farmers in Tanzania by utilizing the very recent survey from agriculture, the National Sample Census of Agriculture (NSCA) 2019/2020. This study aimed to open up the current output level and the contribution of factor inputs, the current efficiency level of agriculture production, and its corresponding determinants. Technical efficiency in this study is analysed by using the stochastic frontier model which has been the most preferred model among agricultural economic researchers (Kongolo, 2021; Missiame et al., 2021; Mwangi et al., 2020). It is undeniable that many other studies have investigated agricultural technical efficiency, however, there is still a need for this study due to several reasons; firstly, Tanzania is not rich in this kind of study that focuses on technical efficiencies of agriculture production or any other activities, second, there is a wide variation of production efficiency in agriculture across and within countries for same or different crops. Similarly, the factors that explain production efficiency across countries and crops also vary as a result it is still important to conduct this study to explore information that best fits Tanzania, third, agriculture is considered to be a backbone of many developing countries including Tanzania and the global is experiencing food insecurity issues due to changing climate and the same, thus it triggers the interest to analyze the current state of production efficiency in Tanzania, and lastly, the study on board utilizes the most recent agriculture survey data to acquire current information based on technical efficient and act as the benchmarking source of knowledge and literature to policy and decision-makers.

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Generally, this study presents an in-depth but precise literature review covering clarification and definition of important terms used in this study, and other relevant materials for reference. The study also presents the theoretical model of which variables are drawn, the data description, empirical model, results including both analytical and simulated results, and then conclusion together with any possible policy implications.

2. LITERATURE REVIEW

In this part we find an understanding of the technical terms that have been used in this study, we assess average efficiency levels across countries and their corresponding determinants.

2.1 Understanding technical terms

In this study, a term that has been mentioned too many times among other things is efficiency/inefficiency. According to the literature included by Miho, (2017), there are three ways of explaining and measuring the level of production efficiencies such as technical efficiency which occurs when maximum output is achieved given a set of limited inputs and allocative efficiency which occurs when factors of production are optimally selected and used, and economic efficiency is the combination of the two. More specifically, economic efficiency explains the ability to produce optimal output while incurring minimum costs given the technology available. This distinction, calls for more clarification about efficiency. Thus, based on Iticha, (2020), in production economics, efficiency refers to the optimal use of available scarce resources in production. Technically, efficiency can be understood in a way that a firm or a production unit can effectively transform or rather convert the given inputs into outputs and significantly respond optimally to economic signals such as price. Production units have a room of improving their productivity by using a limited set of available inputs by just improving or increasing their production efficiency through the adoption of modern technology or employing skilled human capital (Tiruneh & Geta, 2016). On the other hand, we have technical efficiency which is an extension of the general efficiency term. According to Ahmed & Melesse, (2018) and Dijk et al., (2017), technical efficiency (TE), can be defined as the ability of a decision-making unit to covert a given bundle of factor inputs and produce maximum feasible output. Thus, a farm is efficient if it can produce more output with the same set of

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inputs. TE can be measured as the distance to the production or technology frontier which demonstrates best-practice performance (Dijk et al., 2017). In estimating technical efficiency, particularly in the agriculture production value chain, the stochastic frontier approach remains to be the best, most preferred, and dominant method (Akite et al., 2022). Stochastic frontier models are the models which analyse technical inefficiency based on production functions. The assumption is that production units (firms, regions, nations, or any other production unit) produce using common technology and reach the frontier when they create the highest potential output from a given set of inputs (Tenaye, 2020). Further, the Stochastic Frontier Model has two main objectives, one is to estimate the underlying production technology and then measure production technical inefficiency (Ibid).

Agriculture can be easily analyzed by a production function which is composed of total output or yields and its corresponding factor inputs (Tenaye, 2020). Crop yield is a gauge of how much agricultural output is harvested per square meter of land. It is sometimes used as the measure of efficiency as to what extent efficiency factors have contributed to the total crop yield (Dijk et al., 2017). Now, speaking of technical efficiency and or inefficiency, a concept of yield gap arises. The notion of yield gap originated from agronomy and production ecology whereby it refers to the difference between the potential yield and the actual harvest yield at the farm (Ibid). for example, according to Zewdie et al., (2021), production per unit area in African countries taking the example of Ethiopia is very low, this is indeed a yield gap.

Further, other concepts that have been rarely used in this study but are very important to be clarified. These terms include off-farm activities, post-harvest loss, and conservative agriculture. According to Ahmed & Melesse, (2018), off-farm activities are those income-generating activities other than agriculture. These may include but are not limited to handcrafts, household, and non-household manufacturing, mining, construction, transport, quarrying, community service, and repair among others. This concept is included here because they have been noted to be contributing to production efficiency among smallholder farmers (Tamene et al., 2015). On the other hand, Maziku, (2019), defined post-harvest loss (PHL) as a grain loss that occurs after separation from the sire of production to the post-production point where the grains are prepared for consumption. PHL can be on

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quantity and or quality loss of food whereby quality loss may include inferior nutritional value, foodborne diseases, and economic value loss when the yield misses marker opportunity whereas quantity loss includes a loss that can be quantified with metrics (Sugri et al., 2021). PHL is included in this part since it is considered to be among the key indicators of technical inefficiency among smallholder farmers (Akite et al., 2022). Further, a farming method known as conservation agriculture (CA) can restore degraded soils while preventing the loss of arable land. It encourages the preservation of a stable soil cover, little soil disturbance, and plant species diversity (Selejio et al., 2018). CA is included in this study because it has also been noted among key factors that influence crop yields and improve technical efficiency (Sapkota & Joshi, 2021).

2.2 Level of technical efficiency

Production efficiency is not homogeneous because there is a wide variation of production efficiency in agriculture both across and within countries for the same or different crops. This part presents various technical efficient levels across countries on different crops and then TE in Tanzania is presented as well. According to a study conducted by Wang & Hu, (2021) in 12 countries (Argentina, Brazil, and Uruguay (South America), Russia, France, Ukraine, Bulgaria, Poland, Czech Republic, and Hungary (Europe), as well as the US (North America) and South Africa) on corn production, the average technical efficiency revealed was 86.3% which imply that these countries are efficient in producing corn and have room to increase their crop outputs by 13.7% with the same inputs. A cross-sectional study conducted in Kenya focusing on Tomato production efficiency by Mwangi et al., (2020), revealed that Kenya is inefficient in producing tomatoes whereby the technical efficiency (TE) level stood at 39.55%. In Pakistan, Ali et al., (2019), investigated technical efficiency in hybrid maize and found that the average TE stands at 84.3% which implies that, Pakistan still has room to increase hybrid maize production output by 15.7% with the same level of inputs. In Uganda, Akite et al., (2022), investigated the rice production profit efficiency with a single-step stochastic profit frontier approach and found that the mean TE was 59% which implies that Uganda has a clear chance to improve its rice production profit by 41% without changing the factor inputs. Similarly, Missiame et al., (2021), conducted a study

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based on cassava in Ghana and they revealed that the average TE stands at 70.5% with the implication that cassava yield levels could be increased further by 29.5% with the same level of inputs.

In Tanzania, several studies have investigated the level of technical efficiency on various crops in agriculture. According to a Stochastic Frontier Approach study conducted by Kongolo, (2021) in Mwanza Tanzania on technical efficiency and maize production among smallholder farmers, the mean TE stood at 63% whereby producers who operated at a minimal level were at 20% while those producers operated at a maximum level, operated at 91%. According to Selejio et al., (2018) who focused on smallholder agriculture efficiency of adopters and non-adopters of land conservation technologies in Tanzania revealed that, adopters of land management and conservation have a higher TE of 73% compared to their counterparts. This means, that smallholder farmers who practice land conservation are more efficient than their opponents. On the other hand, Miho, (2017), compared Tabora and Ruvuma smallholders technical efficiency and found that Tabora smallholder farmers were more technically efficient with mean technical efficiency of 61% compared to 53% of Ruvuma farmers. This result shows a slight variation, however, their all efficient and they have room of increasing the total yield by 39% and 47% respectively without changing their agricultural inputs.

2.3 Determinants of agriculture production output and technical efficiency

Similar to the level of technical efficiency, determinants of production output and technical efficiency are not homogeneous and they vary across countries and crop types. Kongolo, (2021), who employed a Stochastic Frontier Approach (SFA) identified significantly positive factors that contribute to total crop yields which are labor and farm size. These results implied that, as the number of labor and farm size increases, the total output also increases. Further, seeds and fertilizers were negative and statistically insignificant while the main reason mentioned is that smallholder farmers have less access to fertilizers and improved seeds. On the bit, contrary, Mwangi et al., (2020), investigated Tomato production and employed SFA as well with an addition of a Tobit model and they found that the main factors that increase tomato production output are land size, fertilizers, and seed quantity. This implies that, as the size of land cultivated increases, the quantity of seed used

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increases, and when the farmer uses modern fertilizers is more likely to increase Tomato production output. Tiruneh & Geta, (2016), discovered similar results however to them fertilizer was not statistically significant. Generally, increase in labor (in other studies is referred to as household size as smallholder farmers rely on it), use of tractor assets, an increase in cultivated land, increase in household wealth, off-farm employment, application of fertilizer and herbicides, and the use of improved seeds are the key factor inputs that are significant and are associated with the increase in crop yield among smallholder farmers (Abate et al., 2019; Alwarritzi et al., 2015; Miho, 2017; Tamene et al., 2015; Tenaye, 2020).

On the other hand, technical efficiency has been considered the supreme measure of production efficiency. Factors that are associated with technical efficiency are called efficiency factors. According to Miho, (2017) farmers' age, household size, primary education, and inputs cost were responsible for farmers' technical inefficiency. This means as the farmer's age increase, as the household size increase, as the input costs increases, and when the farmer has acquired primary education, the level of technical efficiency decrease. Further, the same study identified access to credit, owning a capital asset, having a good living condition, and specializing in crop farming as the main activity increases technical efficiency. Differently, according to Alwarritzi et al., (2015), key factors that lead to increased technical efficiency are a farmers-based organization, access to extension services that offer the right information and technical support to farmers, higher education level, and farm diversification. On the other way again, Zewdie et al., (2021) investigated the agriculture TE of smallholder farmers in Ethiopia and found that irrigation plays a significant role in increasing TE among smallholder farmers. Based on the results of Ahmed & Melesse, (2018), farmers who engage in off-farm activities are associated with higher TE compared to their counterparts. Because most smallholder farmers are poor and rely on household labor, Akite et al., (2022), identified that the use of hired labor has resulted in a decrease in technical efficiency since farmers use a lot of money in labor than other inputs. Another exceptional factor that has been identified to be contributing to TE is the application of land management and conservation technologies which in one way or another improve soil fertility and avoid soil erosion and hence increasing TE (Selejio et al.,

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2018). Generally, the most significant determinants of TE among smallholder farmers include age, years of schooling of the household heads (more educated household heads actively adopt new technologies such as improved seed mechanization, soil conservation, and agronomic practices, which could positively influence TE), experience whereby farmers having more years of experience are better placed to acquire the knowledge and skills necessary for choosing appropriate new farm technologies over time which influence TE positively (Abate et al., 2019; Anang et al., 2016; Iticha, 2020; Sapkota & Joshi, 2021). Other factors included the type of seed used whereby improved seeds are associated with higher TE compared to the opposite, and access to extension services whereby the informal sources of teaching, learning process, and immaterial and technical support through access to extension services are assumed to help farmers in updating their farming ways, hence positively influencing TE (Ali et al., 2019; Kongolo, 2021; Missiame et al., 2021; Tenaye, 2020).

3. THEORETICAL MODEL

This study is motivated by the theory of production which explain the output maximization problem and minimization of input requirements costs by using the production function. Production efficiency theory is an extension of production theory and in this study, it acts as a complementary theory. Production efficiency is best analysed by using a stochastic frontier model which combines both output maximization and efficiency.

3.1 Production theory

Production theory as founded by neo-classical economists defined production as the process which involves transforming inputs into output (Sapkota & Joshi, 2021). The main objectives of firms based on this theory are cost minimization, output maximization, and profit maximization. In achieving these production goals, a farmer needs to ensure efficiency in the use of inputs that is technological efficiency, allocative and economic efficiency (Akite et al., 2022). The basic properties of a production function are; Monotonicity whereby a monotonic function is a function that is either entirely nonincreasing or nondecreasing, a production is concave, and a production function considers essentiality whereby a positive input is required to produce a positive output (Dijk et al., 2017). This study limits itself to output

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maximization and therefore, the following production function is simply specified in which output is the function of minimum factors of production and its price.

$$Q = (a_1x_1, a_2x_2 \ldots\ldots a_nx_n) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (i)$$

Where Q represents the total output from smallholder farmers while a_1 , $a_2$represent all necessary input prices and x_1, x_2 represents all necessary factor inputs of production such as land, labor, seeds, fertilizers, and capital among others. According to the theory, the major objective of production efficiency is to provide basic rules about how farmers can effectively utilize inputs to produce output. Further, there any several types of production functions but this study focused on a Cobb-Douglas production function which assumes on constant return to scale (Dijk et al., 2017).

3.2 Efficiency theory

This theory is an extension of a production function for measuring the ability of the producer to employ the most cost minimizing combination of inputs while producing the maximum output given available technology (Miho, 2017). Technically, efficiency can be understood in a way that a firm or a production unit having the ability to effectively transform or rather convert the given inputs into outputs and significantly respond optimally to economic signals such as price (Alwarritzi et al., 2015). In simple language, production efficiency is conducting an operation on the frontier while production inefficiency is the opposite. Production efficiency is usually analysed in three ways such as technical efficiency which occurs when maximum output is achieved given a set of limited inputs, allocative efficiency which occurs when factors of production are optimally selected and used, and economic efficiency which is the combination of the two (Miho, 2017). More specifically, economic efficiency explains the ability to produce optimal output while incurring minimum costs given the technology available. Figure 1 below illustrates production efficiency on a Production Possibility Frontier (PPF).

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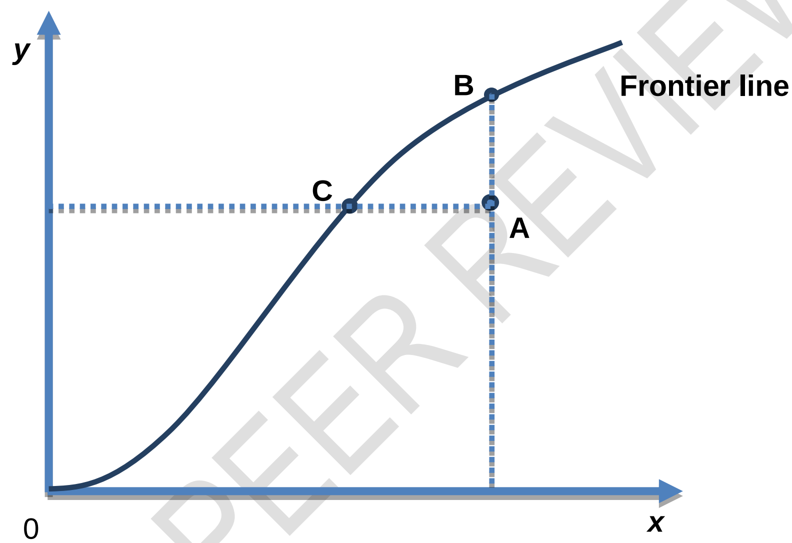

Figure 1: Production efficiency on a Frontier line (PPF). Source: Miho, (2017)

From figure 1 above, production efficiency is presented by points 'B' and 'C' which are points of technical efficiency as production lies on the frontier line (Frontier line) whereas, divergent production from the frontier line of best production indicates production inefficiency as shown by point 'A' because at the same level of inputs (x) a farmer who operates on the frontier at point 'B' achieves potential maximum output (y) compared to the output obtained by firm/farmer at point A, given the same level of inputs (x) producer at B is technically efficient whereas producer at point A is technically inefficient. Technical inefficiency at point A proves the possibility of increasing output production to its maximum using the same level of inputs used by a producer at point B. According to the literature, many factors contribute to technical in/efficiency. These include sex, age of the farmer, household size, education (Tiruneh & Geta, 2016), access to credit (Missiame et al., 2021), capital

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asset (Ali et al., 2019), living conditions, specialization in crop cultivation (Miho, 2017), membership of farm-based organization, irrigation (Anang et al., 2016), off-farm activities (Tenaye, 2020), farming experience (Kongolo, 2021), access to extension service (Mwangi et al., 2020), land conservation practices (Selejio et al., 2018) among others.

3.3 Stochastic production frontier model

Stochastic production frontier models are best explained by using stochastic production frontier functions which were introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977). Because this function may be used to assess how effectively the available technology is being used, a stochastic frontier function is more applicable and acceptable than the deterministic frontier function developed by Farrell (1957) and Aigner and Chu (1968) (Miho, 2017). It takes into account both aspects that the producer cannot control and those that the producer can, making it the favored option by allowing both factors to have an impact on variation between enterprises. Further, this model remains to be the most dominant in explaining farmers' production efficiency (Akite et al., 2022).

According to Pitt & Lee, (1981), Farmers' observed input-output combinations supply the necessary data for measuring technical efficiency since the input-output points on the technically efficient curve reflect the production frontier. Therefore, the cross-sectional frontier production function that is used in this study is estimated below.

$$q_i^* = f(x_i\beta)\exp(\varepsilon_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (ii)$$

$$\varepsilon_i = v_i - u_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (iii)$$

According to Jandrow et al., (1982) q_i^* represents the observed output level of the farmer, i= 1, 2…N, x_i is the vector which stands for inputs quantities by the farmer i, β is the vector of unknown parameters which are to be estimated and ε_i is a composed error to farmer i which is made by the two components $v_i\ and\ u_i$. In equation (iii), a symmetric error that accounts for factors beyond the control of the

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farmer like the weather is represented by v_i and is assumed to be independently and identically distributed while u_i is the non-negative random variable that represents technical efficiency. According to Sapkota & Joshi, (2021), TE can be measured as follows.

$$TE = \frac{q_i}{\exp(x_i\beta + v_i)} = \frac{exp(x_i\beta + \varepsilon_i)}{\exp(x_i\beta + v_i)} = \exp(-u_i) \dots\dots\dots\dots\dots\dots\dots\dots\dots.. (iv)$$

From equation (iv), TE is the ratio of the observed output to the corresponding stochastic frontier output. It measures the output of the farm relative to the output that can be produced by a fully efficient farm using the same input vector. The estimated TE score is categorized in an interval of 0 to 1.

4. DESCRIPTION OF DATA

This study utilized the National Sample Census of Agriculture (NSCA) jointly implemented in 2019/2020 by the National Bureau of Statistics (NBS) and Office of the Chief Government Statistician, Zanzibar (OCGS), in collaboration with Agricultural sector lead ministries (ASLMs). The NSCA's primary intention was to support and fill the information gap necessary for planning and policy formulation by high-level decision-making bodies. Further, it is intended to provide critical and in-depth data indicators needed for monitoring the performance of the Agricultural Sector Development Program Phase II (ASDP II). In addition, the NSCA objective was to provide baseline data on crop production, livestock production, and fish farming.

The dataset was manipulated and modified to fit the objective of this study. Therefore Table 1, presents the descriptive statistics of the selected variables and their characteristics as used in this study. In assessing the relationship between inputs and output, total output in kilogram is used as the dependent variable with the seeds (Kg), fertilizer (Kg), and total land used in production as explanatory variables. The study did not include the labor input as one of the explanatory variables due to two reasons. One is because the dataset didn't include the proper format of the total labor used in the production as a result it is considered a limitation of this study. Further, the study focused on smallholder farmers who are always

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characterized by poverty, and at most, they use family labor, this argument is supported by (Anang et al., 2016). On the other hand, a total of eight efficiency factors were included to measure their effect on the default dependent variable technical inefficiency in the stochastic frontier model. Table 1 presents the descriptive statistics for both, continuous and categorical variables. This study focused on smallholder farmers who are said to depend so much on their households, therefore information about the household heads was substantial. According to the results, the average age of the household head was 49 years while the youngest had 18 years and the oldest with 97 years. From Table 1, on average, Tanzanian smallholder farmers produce 839.8295 kilograms of crop yield. The average quantity of seed used by smallholder farmers stands at 488.7545 kilograms. The average quantity of fertilizers ranges from 0 to 78750 kilograms while standing at 434.5984 kg on average. Further, the average land size used by smallholder farmers during the long rainy season at the time of data collection was 1.540941 hector. In both inputs, the corresponding standard deviations are very large which implies that the data deviated from the mean score of each factor input and total output as well.

*Table*1: Descriptive statistics of the potential variables

PART I: Continuous variables | Inputs and factor inputs					
Variable	**Obs**	**Mean**	**Std. Dev**	**Min**	**Max**
Output (Kg)	53,276	839.8295	3371.023	0	520000
Seed (Kg)	53,278	488.7545	2313.98	0	90,000
Fertilizer (Kg)	11,855	434.5984	2242.008	0	78750
Planted area (Ha)	53,278	1.540941	3.544609	0	465
Age of household age(years)	30,649	49.30885	15.40636	18	97
PART II: Categorical Variables | Efficiency factors					
Variable name	**Category**			**Frequency**	**Percentage**
Education	No Education			17	0.07
	Primary education			20,293	85.61
	Training after primary			157	0.66
	Secondary education			2,268	9.57
	Training after secondary education			306	1.29
	Tertiary/university education			510	2.15
	Adult education			152	0.64

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Membership of farm-based organization	No membership	28031	91.46
	Cooperative	1777	5.80
	Farm organization	706	2.30
	Both	135	0.44
Type of seeds	Local seeds	42,676	80.10
	Improved seed	9,693	18.19
	Both (local & improved)	909	1.71
Agriculture specialization	Crops only	10,993	35.87
	Livestock only	18,981	61.93
	Fish farming	5	0.02
	Pastoralist	661	2.16
	Crops and livestock	10	0.03
Fertilizers used	Organic	7,857	66.28
	Inorganic	3,998	33.72
Access to credit	Have access	1,168	3.81
	Otherwise	29,482	96.19
Access to extension service	Have access	2,196	7.16
	Otherwise	28,454	92.84

On the efficiency side, the study was dominated by household heads with primary education which counts for about 85.61% of the total household heads involved in this study. The majority were not enrolled in both farm-based organizations or cooperative organizations as shown by 91.46% of the total farmers involved in this study (see Table 1). Since agriculture is a very wide field, agriculture specialization was also involved as an efficiency factor with an assumption that those who specialize mostly in crops will be more efficient than their opponents. The descriptive results show that farmers who specialized in crops only were 35.87% and the second largest in the group after farmers who specialized in livestock keeping. The study was dominated by farmers who at most use local seeds and organic fertilizers as shown by 80.1% and 66.28% respectively. Further, smallholder farmers in this study have limited access to both credit services and extension services represented by a higher percentage of non-access as shown in Table 1 above.

Further, the main weakness of the dataset that has been used in this study is the wrong functional and measurement scales. This is reported to be a problem because some variables are coded in a way that they cannot be manipulated further or they just have the wrong function. For example, on the labor use, the dataset

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included responsibility division among members of the household toward agriculture activities but did not include the total number of laborers used. Further, the dataset is too generalized with unclear coding procedures which makes it difficult to focus on a single crop or a single region or zone. On the hand, the dataset is useful especially in the categorization of questionnaires and their dataset in such a way that if a researcher wants to focus on smallholder farmers or larger scale farmers or just the community can have that chance.

5. EMPIRICAL MODEL

The empirical model to estimate TE can take either the Cobb-Douglas production function or the trans-log production function (Selejio et al., 2018). This study assumes a Cobb-Douglas production function (Cobb & H. Douglas, 1928) which is estimated based on the assumption of maximum likelihood estimation (MLE). This function is preferred because it is easy to interpret. Thus function has previously been utilized by (Abate et al., 2019; Miho, 2017). The Cobb-Douglas production function can be expressed as follows.

$$lnoutput = \beta_0 + \beta_1 lnLandsize + \beta_2 lnSeeds + \beta_3 lnFertilizer + (v_i - u_i) \ldots\ldots..(v)$$

Whereby, $lnOutput$ is the log of total harvested output during the long-rainy season in kilograms produced by i^{th} farmer, $lnLandsize$ is the log of the total size of land planted during the long-rainy season in hector by the i^{th} farmer, $lnSeeds$ is the log of the total quantity of seeds used during the long-rainy season in kilograms by the i^{th} farmer, $lnFertilizer$ is the log of the total quantity of fertilizers used during the long-rainy season in kilogram by the i^{th} farmer. The asymmetric error which accounts for factors beyond the control of the farmer like the weather is represented by v_i and is assumed to be independently and identically distributed while u_i is the non-negative random variable that represents technical efficiency.

According to Battese and Coelli, (1995), Inputs and random elements that contribute to production are limited by the output of the potential frontier. The fall is highly a

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result of technical inefficiency which is theoretically identified from the stochastic frontier. Only identifying technical inefficiency is insufficient to address the issue; thus, the sources of technical inefficiency must be identified. Pitt and Lee's (1981)'s method of considering the technical inefficiency of independent variables are taken into account, along with random error and other independent variables. As a result, the technical inefficiency model is given by the following function.

$$U_i = \delta_0 + \delta_1 HHage + \delta_2 Education + \delta_3 FBO + \delta_4 Typeofseed + \delta_5 Typeoffertilizers + \beta_6 Agri - specialization + \delta_7 Credit + \beta_8 Extensionservice + \varepsilon_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(vi)$$

Whereby U_i is the technical inefficiency of the i^{th} farmer, $\delta_0 - \delta_{10}$ is the inefficiency parameter to be estimated. ε_i is the error term in the Ordinary Least Square (OLS) of the technical inefficiency model.

6. PRESENTATION OF RESULTS AND ANALYSIS

This study assumed a Cobb-Douglas production function in analyzing the relationship between the total output and the given inputs. There are two ways of estimating a stochastic frontier model, a single-step approach or a two-step approach, however, a two-step approach is accused of being biased and inconsistency, therefore, a single-step approach is most preferred (Akite et al., 2022) and this study adopted the same by utilizing a truncated normal approach which enables the estimation of a stochastic frontier model in a single step approach (Belotti et al., 2013). Further, this study is based on the output orientation which focuses on the maximization of the total output with the same level of input factors (Ibid).

Before analysis, the primary assumption was that all farmers operate on the frontier which means they are at their full efficiency. According to the results, all three-factor inputs were strongly statistically significant at a 1% level of significance. The number of seeds revealed a strong positive contribution toward the total output of smallholder farmers which implies that a one percent increase in the number of

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seeds in kilogram, results in a 0.059 percent increase in the total output of smallholder farmers. Similarly, the number of fertilizers revealed a strong positive contribution toward the total output of smallholder farmers whereby a one percent increase in the number of fertilizers results in a 0.103 percent increase in the total production output. These results imply that, as the number of fertilizers and seeds increases, the level of output also increases. On the other hand, the size of land used in production revealed a strong positive and significant contribution to the total output. According to the results, as presented in Table 2, with a percentage increase in the size of cultivated land, total output increases by 0.838%. Indeed, land, seeds, and fertilizers remain to be important contributors to all objectives of producers; cost minimization, profit maximization, and sales maximization.

Table 2: Results of a single step stochastic frontier model

Log of output	**Coefficient**	**Std.**	**err.**	**z**	***P*>z**	**95% conf. Interval**
Frontier						
Log of land	0.838	0.016	51.770	0.000***	0.807	0.870
Log of seeds	0.059	0.008	7.080	0.000***	0.043	0.075
Log of fertilizer	0.103	0.010	10.240	0.000***	0.083	0.123
_cons	6.310	0.421	14.990	0.000***	5.485	7.135
Efficiency						
Age	0.002	0.001	2.480	0.013**	0.000	0.004
Education						
Primary	-0.180	0.438	-0.410	0.681	-1.038	0.678
Secondary	-0.185	0.439	-0.420	0.674	-1.046	0.677
Training after sec.	-0.224	0.451	-0.500	0.620	-1.107	0.660
Tertiary/university	-0.177	0.446	-0.400	0.691	-1.051	0.696
Adult education	-0.205	0.459	-0.450	0.654	-1.105	0.694
FBO						
Cooperative	0.388	0.186	2.090	0.037**	0.024	0.752
Farm organization	0.272	0.196	1.390	0.165	-0.112	0.657
Both	0.310	0.180	1.720	0.086	-0.044	0.663
Type of seed						
Improved seed	-0.156	0.024	-6.490	0.000***	-0.203	-0.109
Both (local & improved)	-0.080	0.069	-1.160	0.245	-0.214	0.055
Type of fertilizer						
Inorganic	-0.394	0.030	-12.970	0.000***	-0.453	-0.334
Agriculture specialization						
Livestock only	0.008	0.024	0.320	0.749	-0.039	0.054

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Fish farming	Omitted					
Pastoralist	-0.030	0.092	-0.330	0.744	-0.210	0.150
Crops and Livestock	Omitted					
Access to credit						
Have access	-0.079	0.063	-1.260	0.208	-0.203	0.044
Extension service						
Have access	-0.106	0.047	-2.260	0.024**	-0.198	-0.014
_cons	0.869	0.611	1.420	0.155	-0.328	2.067
U-Sigma						
_cons	-5.153	8.219	-0.630	0.531	-21.262	10.955
V-Sigma						
_cons	-0.566	0.086	-6.570	0.000	-0.735	-0.397
Sigma u	0.076	0.312	0.240	0.808	0.000	239.244
Sigma v	0.754	0.032	23.220	0.000	0.693	0.820
lambda	0.101	0.344	0.290	0.769	-0.573	0.775
Prob > chi2		0.0000				
TE interval		Min =0.319, Max = 0.997				
Mean TE		0.5677				

Benchmark variable for Education= No education, FBO = No membership, type of seed used= local seeds, type of fertilizers = organic, agriculture specialization = crops only, access to credit = no access and access to extension service= no access. **P*<0.1, ***P*<0.05, and ****P*<0.01.

From the efficiency side, a total of eight explanatory variables were estimated which were assumed to affect the default dependent variable which is technical inefficiency. Thus, explanatory variables affecting technical inefficiency are termed efficiency factors. These factors are the age of the household head, education level of the household head, farm-based organization, type of seed and fertilizer used during production, agriculture specialization, irrigation, access to credit, and access to extension service. To avoid the dummy variable trap, all categorical variables were analyzed based on the rule of thumb of 'm-1' whereby" represent the total number of categories of the variable. According to the result as presented in Table 2 above, access to credit, agriculture specialization, and education level turned out to be statistically insignificant however, access to credit and education level, all dummies revealed a negative relationship with technical inefficiency which imply that if education could be significant, it could have contributed to reduce technical inefficiency and increase technical efficiency. Further, some categories within agriculture specialization were omitted and it is assumed that it was due to collinearity. On the other hand, the type of seed and fertilizers used, extension

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service, FBO, and household age yielded significant effects on technical inefficiency in their different categories.

According to the results (see Table 2), for farmers who used improved seeds, their technical inefficiency decreased by 0.156 percent compared to farmers who used local seeds. This result implies that, when farmers use improved seeds, their technical efficiency tends to increase while their technical inefficiency tends to decrease as shown by a negative coefficient (-0.156) which affects technical inefficiency according to the model specification. Inorganic fertilizers revealed a strong and negative effect on the technical efficiency of farmers as shown by a very small P-value (0.000). so technically, farmers who use inorganic fertilizers decrease their technical inefficiency by 0.394 percent compared to farmers who use organic fertilizers. This implies that inorganic fertilizer has a strong contribution to technical efficiency among smallholder farmers in Tanzania. Further, the results show that access to extension service is negative and significant at a 5% significant level which imply that, farmers who have access to extension services decreases their technical inefficiency by 0.106% compared to farmers who do not have access to extension officers. On the other hand, the age of the household head was also significant at a 5% significance level, however, it revealed a positive relationship which implies that, as the age of the household head increases, the technical inefficiency of that farmer also increases and vice versa. Similarly, membership in a cooperative organization revealed a significant and positive relationship toward technical inefficiency which imply that, if a farmer is a member of a cooperative organization his or her technical efficiency decreases by about 0.38%.

Further, the average technical efficiency among smallholder farmers in Tanzania is 56.72 percent which ranges from 31.9 to 99.7 percent. This is just a little forward from the satisfactory boundary of TE of 50% which we would consider technical inefficiency, therefore having the TE level of 56.72 is not something to celebrate.

7. DISCUSSION OF FINDINGS

The objective of this study was to determine the current technical efficiency level and its potential determinants among Tanzania smallholder farmers. The primary hypothesis was that Tanzania's smallholder farmers are technically inefficient. Therefore, to test this hypothesis, the study followed previous researchers (Abate et

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al., 2019; Akite et al., 2022; Selejio et al., 2018; Zewdie et al., 2021) in estimating the stochastic frontier model that determines the level of technical efficiency and then presents the contribution of efficiency factors toward TE. Before the execution of the stochastic frontier model, a descriptive analysis was conducted (See Table 1) to obtain the basic characteristics of the utilized data. All basic characteristics of the dataset and the variables of interest have been discussed in the description section; however, more emphasis is given to four key factors when it comes to crop cultivation. These factors are types of seeds and fertilizers used, access to credit, and access to extension service. According to the results, 80% of Tanzanian smallholder farmers used local seeds while only 18% used improved seeds as illustrated in Figure 2 below. This result aligns with Tiruneh & Geta, (2016) who argued that smallholder farmers do not attain higher performance due to limited access to improved seeds attributed to their severe poverty.

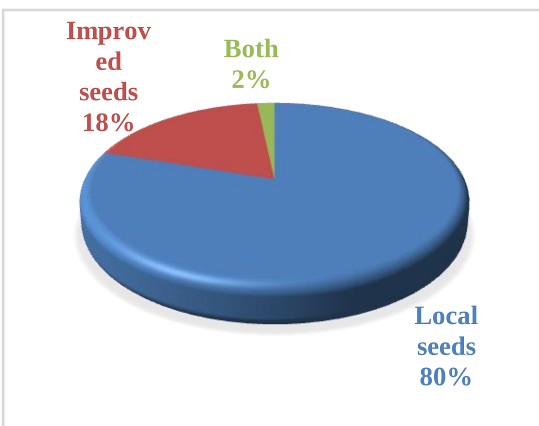

Figure 2: Types of seeds used

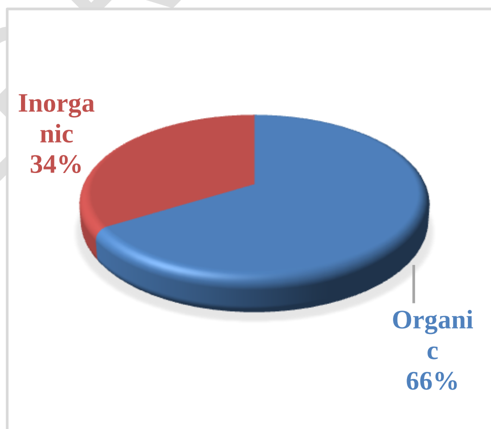

Figure 3: Types of fertilizers used

Further, 66% of Tanzanian smallholder farmers revealed that they use organic fertilizers (natural fertilizers) while 34% (Figure 3) were using more chemical or artificial fertilizers collectively known as inorganic fertilizers. This result implies that smallholder farmers do not have enough income to afford improved or inorganic fertilizers. Anang et al., (2016), justify that smallholder farmers who most are located in rural areas are poor and do not have much access to improved agriculture practices such as inorganic fertilizers.

On the other hand, based on the literature, access to credit and extension services are key important third-party factors that contribute to the overall production efficiency. Sapkota & Joshi, (2021) argued that, extension service ac is an informal source of teaching, learning, and immaterial and technical support which helps farmers in updating their farming ways into modern practice and hence higher production efficiency. On the other hand, Missiame et al., (2021), suggested that farmers who have access to credit from banking institutions are more likely to be efficient because it provides them with the source of capital that they can use to finance their activities. However, the descriptive results shows that only 4% and 7% had access to credit and extension service respectively as illustrated on figure 4 and 5 below.

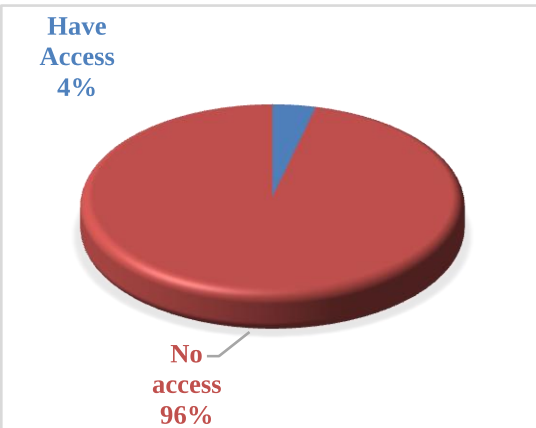

Figure 4: Accessibility to credit

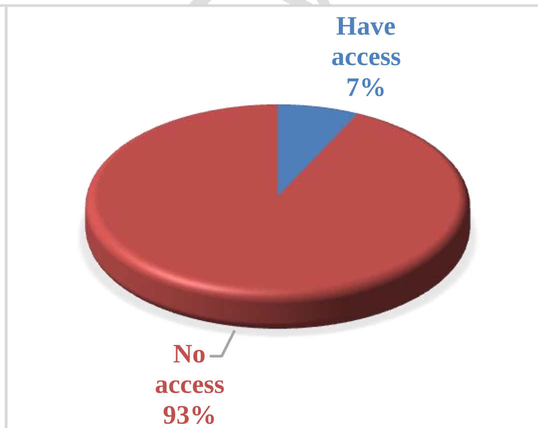

Figure 5: Accessibility to

A thorough conclusion from this result is that Tanzanian smallholder farmers have limited access to both credit and extension services as a result, the overall technical efficiency was expected to be low.

As described earlier, this study adopted a single-step approach in estimating the stochastic frontier model and it was estimated based on the truncated normal distribution. The advantages of the single-step stochastic frontier model are that it estimates with consistency, reduces biasness, and presents both frontier model and efficiency effect at once (Belotti et al., 2013). Thus, the data were analysed, summarized, and presented in Table 2.

On the frontier model which focused on the relationship between input and outputs, all inputs used (labor, seeds, and fertilizers) were statistically significant and positive which implies that labor, seeds, and fertilizers remain to be the most important factors contributing to the growth of overall production output. These results justify the findings of (Alwarritzi et al., 2015; Mwangi et al., 2020; Tenaye, 2020). However, other studies were a bit contrary. For example, Kongolo, (2021) discovered that seeds and fertilizers are not statistically significant in contributing to total production output while according to him only farm size and labor were significantly contributing to the total output of smallholder farmers.

Tiruneh & Geta, (2016), who conducted a technical efficiency analysis of Wheat in Ethiopia, revealed that improved seeds are the gemstone for maximum output given a set of limited inputs, thus this paper has aligned with these findings and therefore it provides justification that, it is undeniably, the improved seed has a significant contribution toward farmers production efficiency. Further, (Ibid) aligned with this study again in measuring the effect of inorganic fertilizers on technical efficiency whereby they found that inorganic fertilizers alongside other factors, significantly reduce technical inefficiency among smallholder farmers.

This study has revealed a significant effect of extension service on technical efficiency whereby farmers exposed to extension officers tend to have low technical inefficiency compared to their opponents. However, Tamene et al., (2015), found a contrary result based on the impact of extension service on TE. According to them, extension service reduces total yield and the overall TE while the main reason given is that, the number of extension officers is low compared to the number of farmers. On the other hand, other studies aligned with our results for example Sapkota & Joshi, (2021) in Nepal, found that extension offers knowledge, skills, and technical support to farmers and consequently reduces their inefficiency, Abate et al., (2019) found that access to extension service increases technical efficiency of red pepper farmers, and Ali et al., (2019) in Pakistan, found that being exposed to extension officers increases the production output of hybrid maize growers by using minimal output, hence favorable TE. Despite the proven contribution of extension service, Zewdie et al., (2021) argued that extension service is still poor, especially in developing countries taking the example of Ethiopia.

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It is for certain a normal thing to agree to disagree. According to the results, the age of the household head and membership in the cooperative organization was significant but with a positive relationship implying that, as the age of the household head increase, his/farmers' production efficiency decreases. Similar to membership in a cooperative organization such that, when a farmer is a member of the organization, his/her production efficiency decreases. On the contrary, Anang et al., (2016), revealed that farmers who are a member of the farm-based organization and cooperatives as said to be more efficient compared non-members. Further, other researchers have found that age harms technical inefficiency whereas as the age of a farmer increases, he gains more experience and therefore technical inefficiency decreases (Iticha, 2020; Miho, 2017; Sapkota & Joshi, 2021).

Generally, according to the study findings as presented in Table 2, the average technical efficiency of smallholder farmers in Tanzania is 56.72% which ranges from 32% to 99.8% as predicted by a Battesse and Coelli (BC) model (1988) through *jams* STATA command as suggest by Jandrow et al (1982).

Table 3: Level of technical efficiency (TE)

	Obs	**Mean**	**Std. Dev.**	**Min**	**Max**
Battesse and Coelli Model (1988)	4497	0.5672	.106	0.32	0.998

This level of efficiency implies that smallholder farmers still can increase their output level by 43.3% with the same factor inputs. Since the TE level is above 50% it can be concluded that Tanzanian smallholder farmers are efficient in producing equicrural output by 56.72%. This TE level is not far different from other TE levels estimated by other researchers in Tanzania. Selejio et al., (2018) found a 73% TE level among maize smallholder farmers by utilizing the national panel data while Kongolo, (2021) found a 63% TE level of smallholder farmers in the Mwanza region of Tanzania. Thus, these few pieces of evidence suggest that the level of TE found in this study is relevant and significant.

8. CONCLUSIONS

A single-test approach was used with the aid of truncated normal distribution in assessing the contribution of factors of production such as land size, seeds, and fertilizers toward the total production output. And then on the same estimation to

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include the efficiency effect where the age of the household head, his education level, type of seeds and fertilizer used, access to credit and extension services, agriculture specialization, and farm-based organization were assumed to be influencing farmers' technical inefficiency. The results revealed that all factors of production that were included for the analysis (cultivated land, seeds, fertilizers), were strongly positive and significant toward production output. On the efficiency side, improved seeds, inorganic fertilizers, and access to extension services were noted to be decreasing farmers' technical inefficiency and increasing technical efficiency. Further, the age of the household head and membership of cooperative organizations among farmers increases technical inefficiency. Contrary, education, access to credit, and agriculture specialization turned out to be statistically insignificant. Therefore, it is recommended that policy and decision-makers put more effort into improved seeds and improved fertilizers when designing agricultural interventions to advance the sector.

From the economic point of view, the results of this study are significant and useful despite the insignificant of some variables that were expected to be statistically significant. The findings of this study generalize the overall nature and behaviors of smallholder farmers in Tanzania concerning their production efficiency, as a result, it is emphasized that policy and decision makers go ahead and utilize these results in designing both economic and non-economic intervention in the agriculture sector. In a nutshell, food security is an important and undeniable topic among policymakers. Thus, there are other areas direct or indirect related to food security that needs the researcher’s attention. These areas include technical efficiency of irrigation schemes among large and small farmers in Tanzania, and post-harvest loss and its effect on production efficiency and food security as well. Indeed, these areas and the likes require immediate attention from researchers to create enough reference knowledge for policy and decision-makers and to address food security indicators. Therefore, if time could allow, I would have jumped into it.

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