Assessing Production Efficiency by Farm Size in Rwanda: A Zero-inefficiency Stochastic Frontier Approach

Jules Ngango (ngajules2@gmail.com)

Department of Agricultural Economics, Chungnam National University, Daejeon 34134, South Korea

https://orcid.org/0000-0002-9584-5318

Seungjee Hong

Chungnam National University

Research

Keywords: technical efficiency, farm size, stochastic production frontier, zero-inefficiency, Rwanda

Posted Date: October 2nd, 2020

DOI: https://doi.org/10.21203/rs.3.rs-84178/v1

Version of Record: A version of this preprint was published at Scientific African on March 1st, 2022. See the published version at https://doi.org/10.1016/j.sciaf.2022.e01143.

Title Page

The full title:

Assessing production efficiency by farm size in Rwanda: a zero-inefficiency stochastic frontier approach

Author information

Author names:

Jules Ngango* and Seungjee Hong

Affiliations and e-mail addresses:

Jules Ngango: *Department of Agricultural Economics, Chungnam National University, Daejeon 34134, South Korea*

E-mail: ngajules2@gmail.com

Seungjee Hong: *Department of Agricultural Economics, Chungnam National University, Daejeon 34134, South Korea*

E-mail: hseungj@cnu.ac.kr

Corresponding author

***Correspondence**: Jules Ngango, Tel: +82-10-4966-4304, E-mail: ngajules2@gmail.com

Blinded Manuscript

Assessing production efficiency by farm size in Rwanda: a zero-inefficiency stochastic frontier approach

Abstract

This study investigates the relationship between farm size and technical efficiency for maize production in Rwanda. Since levels of technical efficiency tend to vary considerably across farms in sub-Saharan Africa, with a mixture of both inefficient and fully efficient farms, the use of the conventional stochastic frontier method is not appropriate. In this paper, we apply a zero-inefficiency stochastic frontier method that manages both efficiency and inefficiency in the studied sample. The average technical efficiency of maize farms for the full sample is estimated at 0.64, demonstrating that maize output can be improved by approximately 36% without increasing the proportion of farm inputs used. Regarding the relationship between farm size and technical efficiency, the study results show a positive relationship between farm size and technical efficiency for maize production in Rwanda. Thus, the enforcement of land reforms such as land consolidation and enhanced aggregate productivity growth are needed. The results also indicate that education, cooperative membership, extension services, access to credit, off-farm income, land tenure, and livestock ownership have significant and positive effects on technical efficiency.

Keywords: technical efficiency; farm size; stochastic production frontier; zero-inefficiency; Rwanda

1. Introduction

Increased agricultural productivity has been identified as a major solution that can lead to improved food security, poverty reduction, and economic growth in Sub-Saharan Africa (SSA) (Julien et al. 2019). In recent decades, agrarian policies adopted in most SSA countries have supported the promotion of agricultural technologies and the efficient use of scarce land resources to achieve sustainable farm yields (Ali and Deininger 2015). Agricultural production across SSA countries is largely dominated by small-scale farming (Julien et al. 2019). In particular, Rwanda, the most densely populated country in Africa, has an average landholding level of only approximately 0.72 hectares per household (Ali and Deininger 2015). Moreover, smallholder farming in Rwanda is usually not capital intensive, i.e., most smallholder farm operators do not use farm machinery in their agricultural activities and are characterized by low crop productivity (Ali et al. 2015).

Recently, issues related to small-scale farm sizes, land fragmentation, and low crop productivity in Rwanda have been a priority to policymakers, research institutions, and nongovernment organizations (Ali and Deininger 2015). Khataza et al. (2019) indicated that the efficient management of scarce land resources devoted to farming activities constitutes an essential instrument towards the improvement of agricultural productivity and food security. In an attempt to achieve food security, the Rwandan government has adopted a land consolidation program to reallocate fragmented small-scale farm plots to form large-scale parcels for more rational landholding (Ansoms et al. 2008). These institutional changes are expected to increase economies of scale (Ali and Deininger 2015).

An enduring debate in the agricultural economics and rural development literature concerns the relationship between farm size and agricultural productivity. This relationship has significant implications for agricultural and land policies (Khataza et al. 2019; Rada and Fuglie 2019; Zhong et al. 2019). However, empirical evidence from previous studies suggests that it

remains unclear whether small-scale farms are more productive than large-scale farms (Barrett et al. 2010; Gautam and Ahmed 2019; Julien et al. 2019; Khataza et al. 2019; Kimhi 2006; Rada and Fuglie 2019). Numerous studies have confirmed inverse relationships between farm size and various agricultural productivity measures, such as technical efficiency (TE) and total factor productivity (TFP). In the context of agricultural production in SSA, such inverse relationships have recently attracted considerable attention from policymakers and researchers, mainly due to their controversial implications for land reforms and agricultural policies (Desiere and Jolliffe 2018). In this regard, the existence of an inverse relationship between farm size and productivity implies that land redistribution should be considered an appropriate land reform that can improve the managerial performance (i.e., TE) of farmers and hence agricultural productivity (Julien et al. 2019). On the other hand, empirical studies have found a positive relationship between farm size and productivity (Kimhi 2006; Muyanga and Jayne 2019; Xin et al. 2016), suggesting that land consolidation can be considered an appropriate policy means to improve productivity (Desiere and Jolliffe 2018).

In the literature, variations in empirical findings on the relationship between farm size and productivity are mainly attributed to the use of different analytical approaches (Barrett et al. 2010; Gautam and Ahmed 2019; Julien et al. 2019; Khataza et al. 2019; Muyanga and Jayne 2019; Zhong et al. 2019). Some empirical studies have applied the ordinary least squares (OLS) model. In contrast, other studies have used frontier-based approaches such as the stochastic frontier (SF) model to examine the relationship between farm size and productivity. Typically, these conventional approaches assume that all farms in a sample are inefficient, implying that the probability of observing fully efficient farms is zero (Abdulai and Abdulai 2016). Nevertheless, evidence from the literature indicates the presence of both inefficiency and full efficiency among farmers in SSA (Abdulai and Abdulai 2016; Theriault and Serra 2014). Thus, the use of the

conventional SF model without accounting for both inefficiency and full efficiency may result in biased estimates, which may also lead to inappropriate policy making (Abdulai and Abdulai 2016). Kumbhakar et al. (2013) introduced a zero inefficiency stochastic frontier (ZISF) model to manage this assumption of inefficient behavior.

This study uses the ZISF model to investigate the relationship between farm size and TE for maize production in Rwanda. In Rwanda's context, only three studies have attempted to investigate the relationship between farm size and productivity (Ali and Deininger 2015; Ansoms et al. 2008; Byiringiro and Reardon 1996). However, none of those studies apply frontier-based approaches that are known to manage productive inefficiency. Our study contributes to the existing literature by demonstrating the application of the ZISF model to examine the farm size-productivity relationship.

The remainder of this paper is structured as follows. Section 2 presents the background on land problems in Rwanda. Section 3 presents the methods used with a detailed discussion of the conventional SF and ZISF models. Section 4 provides a description of the data and summary statistics. Section 5 presents the empirical results and a discussion. The final section concludes with a summary of the study's findings and policy implications.

2. Background on land and productivity in Rwanda

Land remains a valuable asset that determines to an exceptional level the social status and the economic well-being of households in Rwanda and most parts of sub-Saharan Africa (Holden and Otsuka 2014; Muchomba 2017; Pritchard 2013). Land tenure reforms have been given considerable attention in the Poverty Reduction Strategy Papers of several African countries (Place 2009). In particular, the secured land property rights are among the top priorities of the

development agenda of the Rwandan government because, conceptually, improving it may foster agricultural investment and production growth (Bambio and Bouayad Agha 2018).

2.1. Land related issues in Rwanda

Land fragmentation and land scarcity are becoming significant threats to the improvement of agricultural production and food security in Rwanda (Ntihinyurwa et al. 2019). In particular, Rwanda is the most densely populated country in Africa, and a large number of the population (about 83%) live in rural areas (Pritchard, 2013).[1] Rwanda's population pressure has also resulted in smaller plots and fragmented landholdings (Bizoza 2014). Place (2009) argues that land fragmentation constitutes a significant obstacle to agricultural development because it hinders agricultural mechanization tools such as tractors and harvesters. Land fragmentation can also discourage the adoption of irrigation technologies and other long-term investments on land that are only profitable on a larger scale (Tran and Vu 2019). Given that plot size has been diminishing over the years, land distribution in Rwanda is also highly unequal with a large portion of land being owned by a minority of wealthier elite including politicians, business people, and civil servants from urban areas (Musahara and Huggins 2005; Pritchard 2013). Inequality in land distribution is a major policy issue for the government of Rwanda, as it may influence land-related conflicts and poverty (Musahara 2006).

Bizoza (2014) also noted that population pressure had induced shifts in land use, resulting in the cultivation of fragile marginal land on steep slopes and deforestation. In general, the Ministry of Agriculture and Animal Resources (MINAGRI) acknowledges that considerable land

[1] According to the fourth Integrated Household Living Conditions Survey, Rwanda has a population density of about 462 people per square kilometer.

degradation due to soil erosion has significantly reduced agricultural production (Minagri 2018). Recently, soil conservation efforts have focused on the building of terraces, hedges, and agroforestry (Pritchard 2013).

2.2. The relevance of farm size-productivity relationship in the context of Rwanda

Rwandan economy relies heavily on the agriculture sector, with about 75% of the economically active population employed in agriculture (World 2018). The subsistence-based agriculture sector of Rwanda is dominated by small-scale farms (Ali and Deininger 2015). Moreover, the high population growth exerts severe pressure on arable land, which is a constraint to agricultural productivity (Julien et al. 2019). Consequently, the current strategic plan for agricultural transformation has a target of addressing the issue of low crop productivity through crop intensification and land consolidation programs (Ansoms et al. 2008).

Regarding the above context of Rwanda's agriculture, empirical studies investigating the relationship between farm size and productivity are relevant. The conclusions about the category of land size (i.e., whether small-scale or large-scale) that is more efficient and productive, would provide useful insights to land reforms and agricultural policies directed towards the increase of agricultural productivity and food security. For instance, efforts to promote land consolidation should be prioritized if large farms are found to be more efficient than their smaller counterparts (Khataza et al. 2019).

3. Methodology

According to Farrell (1957) classical proposition, TE is one of two components of total economic performance and allocative efficiency (Coelli et al. 1998).[2] Typically, in the literature, two empirical approaches have been broadly used to estimate TE. The first is DEA, which is a nonparametric approach involving the use of linear programming techniques (Khataza et al. 2019; Liu et al. 2017). Although efficiency estimation using DEA does not impose a functional form on the data, this approach fails to effectively address statistical noise that is likely to affect the accuracy of estimates (Khataza et al. 2019; Liu et al. 2017). Alternatively, parametric models such as the SF model are also widely used to estimate TE. Coelli et al. (1998) suggest that the SF approach, which involves econometric methods, is the most appropriate approach to TE analysis in agricultural production studies, as the SF model can address statistical noise (outliers). Furthermore, the SF model allows for statistical tests of hypotheses regarding parameter estimates and for the measurement of TE across farms of different sizes (Julien et al. 2019). Consequently, we adopt the SF model in the present study.

3.1. Stochastic production frontier model

The general form of the conventional SF model is as follows:

$$Y_i = f(X_i; \beta) \cdot exp(\varepsilon_i), i = 1, 2, \dots \dots, N. \quad (1)$$

where Y_i represents the output of farm i, and $f(\cdot)$ is the production function (e.g., Cobb–Douglas or translog). X_i denotes a vector of inputs, and β is a vector of unknown parameters to be estimated. Note that composite error term ε_i is made up of two components:

$$\varepsilon_i = v_i - u_i, \quad (2)$$

[2] The TE of a farm reflects its ability to achieve the maximum output possible from a given set of inputs.

where v_i is a random error term representing statistical noise due to unobserved factors beyond the producer's control (e.g., weather fluctuation) and measurement errors. As noted by Coelli et al. (1998), the random error component is assumed to be normally distributed with a mean of 0 and constant variance of σ_v^2, i.e., $[v_i \sim N(0, \sigma_v^2)]$. The second component is nonnegative inefficiency error term u_i, which is assumed to follow a positive truncated normal distribution (i.e., $u_i \geq 0$) with a mean of μ and variance of σ_u^2, i.e., $u_i \sim N^+(0, \sigma_u^2)$.

The specification of technical inefficiency (u_i) can then be written as:

$$u_i = z_i\delta + \omega_i, \tag{3}$$

where z_i denotes a set of farm- and household-specific covariates, and δ is a vector of parameters to be estimated.

3.2. Zero inefficiency stochastic frontier model

Following Kumbhakar et al. (2013), the ZISF production model is specified as follows:

$$\begin{aligned} &ZISF \rightarrow y_i = x_i'\beta + v_i \text{ with probability } p, \text{ and} \\ &y_i = x_i'\beta + (v_i - u_i) \text{ with probability } (1-p) \end{aligned} \tag{4}$$

where y_i represents the output of farm i, x_i is a vector of inputs, β is a vector of unknown parameters to be estimated, p is the probability of a farm being fully efficient, and $(1-p)$ is the probability of a farm being inefficient. The composed error term in the ZISF model is given by $v_i - u_i[1 - 1(u_i = 0)]$ where $p = 1(u_i = 0)$.

The density function of the convoluted error term of the ZISF model is defined as:

$$f(\varepsilon|x) = \left(\frac{p}{\sigma_v}\right) g\left(\frac{\varepsilon}{\sigma_v}\right) + (1-p)\left[\frac{2}{\sigma} g\left(\frac{\varepsilon}{\sigma}\right) G\left(-\varepsilon\frac{\lambda}{\sigma}\right)\right] \tag{5}$$

where g and G are the normal probability density and normal cumulative distribution functions, respectively, $\sigma^2 = \sigma_u^2 + \sigma_v^2$, and $\lambda = \sigma_u/\sigma_v$.

For the estimation of the inefficiency function in the ZISF model, we adopt the approach developed by Jondrow et al. (1982), which postulates that the conditional density function of inefficiency u given ε is zero with probability p and truncated normal $N_+(\mu_*, \sigma_*^2)$ with probability $1-p$. This function is expressed as:

$$f(u|\varepsilon) = \frac{g[(u-u_*)/\sigma_*]}{\sigma_* G(-\varepsilon\lambda/\sigma)} \tag{6}$$

where $\mu_* = -\varepsilon\sigma_u^2/\sigma^2$ and $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$. From the specification in Equation (6), the conditional mean estimator for inefficiency in the ZISF model is given by:

$$E(u|\varepsilon) = (1-p)\frac{\sigma\lambda}{1+\lambda^2}\left[\frac{g(-\lambda\varepsilon/\sigma)}{G(-\lambda\varepsilon/\sigma)} - \frac{\lambda\varepsilon}{\sigma}\right] \tag{7}$$

Here, the measurement procedure entails the replacement of unknown parameters with their maximum likelihood (ML) estimates, and error term ε should be replaced by its residuals $\hat{\varepsilon}_i$. In addition, inefficiency in the ZISF model can be estimated by constructing the posterior estimates of inefficiency, which are expressed as:

$$\check{u}_i = (1-\check{p}_i)\check{u}_i \tag{8}$$

where $\check{p}_i$ denotes the posterior estimate of the probability of full efficiency, which is written as:

$$\check{p}_i = \frac{(\hat{p}_i/\hat{\sigma}_v)g(\hat{\varepsilon}_i/\hat{\sigma}_v)}{(\hat{p}_i/\hat{\sigma}_v)g(\hat{\varepsilon}_i/\hat{\sigma}_v) + (1-\hat{p}_i)(2/\hat{\sigma})g(\hat{\varepsilon}_i/\hat{\sigma})G(-\hat{\varepsilon}_i/\hat{\sigma}_0)} \tag{9}$$

These posterior estimates of inefficiency are influenced by farm and household characteristics.

To test for zero inefficiency, we use the pseudolikelihood ratio (PLR) test. The PLR test is represented as $PLR = -2(L_N - L_{ZI})$ where L_N denotes the log-likelihood of the normal linear model estimated using OLS and L_{ZI} denotes the log-likelihood of the ZISF model. As noted by Kumbhakar et al. (2013), the PLR test has an asymptotic distribution that constitutes a 50:50 mixture of inefficient χ_0^2 and fully efficient χ_1^2 distributions. In testing for zero inefficiency, the rejection of the null hypothesis of full efficiency (i.e., $H_0: p = 1$) indicates the presence

efficiency in the ZISF model and of inefficiency in the conventional SF model (Abdulai and Abdulai 2016).

3.3. Empirical specification

The empirical specification of SF models typically uses Cobb-Douglas or translog functional forms. The Cobb-Douglas functional form is the most commonly used in the literature due to its simplicity and consistency with key properties of production economic theory (Julien et al. 2019). However, the Cobb-Douglas form requires that the partial elasticities of production and returns to scale have the same value across all data points (Julien et al. 2019; Khataza et al. 2019). In contrast, the translog does not impose restrictions on partial elasticities of production or returns to scale. Nevertheless, it fails to maintain consistency with the key properties of production economic theory such as monotonicity and quasi-concavity (Julien et al. 2019). Thus, to ensure flexibility in the estimated parameters and consistency with production economic theory, we adopt the Cobb-Douglas functional form, which is specified as follows:

$$\ln Y_i = \beta_0 + \sum_{j=1}^{4} \beta_j \ln X_{ij} + (v_i - u_i), \quad (10)$$

$$u_i = \sum_{d=1}^{11} \delta_d Z_{id} + e_i \quad (11)$$

where Y_i is the production output of maize, X_{ij} is the jth input of the ith farmer, and β_j and δ_d are the unknown parameters to be estimated. We include four inputs, namely, land, labor, fertilizer, and seeds.

Additionally, we include eleven determinants of technical inefficiency (Z) based on relevant literature and data availability. These variables include age, gender, household size, education, cooperative membership, access to credit, extension services, slope, land tenure, off-farm work, and livestock ownership.

4. Data and summary statistics

4.1. Data and variable definition

The data used in this study are cross-sectional data collected through a household survey conducted in the Eastern Province of Rwanda from July to August 2019. A representative sample of this study consists of 351 household farmers randomly selected from three districts, namely, the Bugesera, Kirehe, and Nyagatare districts of the Eastern Province of Rwanda. This sample was drawn using a multistage sampling technique. First, in consultation with the Ministry of Agriculture and Animal Resources (MINAGRI), three districts were purposively selected based on their intensive maize production levels. In the second stage, four administrative sectors were randomly selected from each district due a predominance of maize farmers. In the third stage, a random sample of respondents was selected from each sector for personal interviews. Based on the list of farmers obtained from each extension officer at the sector level, a total of 1197 individual farm household units were counted and recorded in all 12 sectors. Due to limited resources and time, 34 respondents were randomly selected from each sector, resulting in a total sample of 408 household farmers. However, after cleaning the collected data, we ended up with a total sample of 351 household farmers.

Respondents were interviewed using a structured questionnaire by trained and experienced research assistants. The survey collected detailed information on maize production outputs and on inputs used in the production process during the 2018–2019 crop season. Information on the socioeconomic characteristics of the households and on institutional and farm-specific characteristics was also collected.

Table 1. Description of variables used in the analysis

Variable	Definition
Yield	Total maize production in kilograms per hectare (kg per ha)
Land	Total land area planted with maize crops (ha)
Labor	Labor input including both hired and family labor (person-days per ha)
Fertilizer	Quantity of fertilizer used (kg per ha)
Seed	Quantity of seeds used (kg per ha)
Age	Age of household head (years)
Gender	Dummy variable equal to 1 if the household head is male and 0 otherwise
Education	Years of formal education
Household size	Total household size (number of persons)
Coop. membership	Dummy variable for cooperative membership equal to 1 if a farmer is a member of the cooperative and 0 otherwise
Extension	The frequency of extension visits (number per year)
Land tenure	Dummy variable for land tenure equal to 1 if the farmer owns the land and equal to 0 when land is rented
Credit access	Dummy variable equal to 1 if a farmer has access to credit and 0 otherwise
Off-farm income	Dummy variable for off-farm income equal to 1 if a farmer has other sources of off-farm income and 0 otherwise
Slope	Dummy variable for slope equal to 1 if land is characterized by steep slopes and 0 otherwise
Livestock	Amount of livestock owned in tropical livestock units (TLUs)

Note: TLUs across various categories of livestock are computed as follows: 0.7 for cows; 0.45 for heifers; 0.1 for goats; 0.1 for sheep; 0.01 for chicken; and 0.2 for pigs (Zeweld et al. 2015).

In general, agricultural production in Rwanda is not capital intensive because most of the farmers do not use agricultural machinery (e.g., tractors) in their farming activities. Indeed, the variable inputs included in our analytical model are land, labor, fertilizer, and seeds (see Table 1). The land input is measured as the total farm size in hectares (ha) planted with maize during the

2018–2019 crop season. Labor input (i.e., hired and family labor) used to perform all farm operations during the 2018–2019 crop season is measured in person-days per ha. Typically, in the majority of Sub-Saharan African countries, the labor force consists of men, women, and children. Hence, following Khataza et al. (2017), labor is defined in terms of adult equivalent units using the following conversion factors: one adult male (at least 15 years of age, working on a full day-basis) represents one person-day. An adult female working on a full day-basis represents 0.8 person-days, and one child (5–14 years) working for a full day represents 0.5 person-days (Julien et al. 2019; Khataza et al. 2017). Fertilizer input is measured as the total quantity of di-ammonium phosphate and urea in kilograms per ha applied on the farm during the 2018–2019 crop season. Seed input is expressed as the quantity in kilograms per ha of maize seeds used in farm production during the 2018–2019 cropping season.

Furthermore, the explanatory variables used in the analysis as the determinants of technical inefficiency are presented in Table 1. Household demographic variables such as age, education, household size, and gender may influence the TE. For instance, higher levels of education are expected to improve farmers' managerial performance which can also enhance TE's level (Julien et al. 2019). A dummy variable for cooperative membership is included to assess the effect of cooperatives on TE. Based on the empirical evidence from previous studies (Abdul-Rahaman and Abdulai 2018; Helfand and Levine 2004; Mar et al. 2018; Mwalupaso et al. 2019), we expect the participation in farmers' cooperatives to have a positive effect on TE. Other institutional factors, such as extension services and access to credit, are considered to be an important determinant of farm TE. They are both expected to be positively correlated with TE. The variable slope is expressed as a dummy variable equal to one if the farm is located on a steep slope and zero otherwise. Typically, the slope variable is expected to be negatively correlated with the TE due to the evidence that steep slopes tend to face problems related to irrigation

development, mechanization, and soil erosion (Julien et al. 2019). The remaining explanatory variables are land tenure, off-farm income, and livestock ownership.

4.2. Summary statistics

Table 2 presents the mean values and standard deviations of all variables used in the present study for the full sample and across each of the three considered farm size categories. Following Byiringiro and Reardon (1996) suggestions, the three categories of farm size in Rwanda are defined as (1) small-scale farms with land area of less than 1 ha; (2) medium-scale farms with land area of 1–2.5 ha; and (3) large-scale farms with land area of over 2.5 ha. The summary statistics reported in Table 2 show considerable differences between the three farm size categories. Indeed, the average yield is highest (2285 kg/ha) for large-scale farms while small-scale farms have the lowest average yield (1766 kg/ha). In terms of production inputs used per hectare, the average amount of fertilizers used on large-scale farms is higher than that used on medium- and small-scale farms by approximately 9.3% and 22.5%, respectively. Similarly, on average, large-scale farms use more maize seeds per hectare than medium- and small-scale farms. Regarding the average use of human labor, large-scale farms use labor more intensively than medium- and small-scale farms.

In our sample, the socioeconomic characteristics of households vary significantly across farm size categories. The summary statistics reported in Table 2 indicate that educational attainment is generally low (i.e., below six years of primary education). By comparison, large-scale farmers have completed more education than medium- and small-scale farmers. The majority of households (69%) in the study area have male heads, and their average age is approximately 47 years. On average, farmers with large-scale farms secure greater access to extension services and credit than their counterparts with medium- and small-scale farms (see

Table 2). Moreover, membership in agricultural cooperatives is higher among large-scale farmers (62%) than for medium- (53%) and small-scale farmers (36%). In addition to the above variables, other variables such as livestock ownership, land tenure, slope, and off-farm income exhibit clear differences between the three farm size categories. Differences in socioeconomic and farm characteristics can be significant sources of dissimilarity in farm managerial performance (i.e., TE) across farm size categories (Julien et al. 2019; Muyanga and Jayne 2019).

Table 2. Summary statistics of all variables by farm size category

Variables	Small-scale farms (<1 ha; n = 109)	Medium-scale farms (1–2.5 ha; n = 174)	Large-scale farms (>2.5 ha; n = 68)	Full sample (n = 351)
	Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)
Yield	1766.64 (236.38)	2013.27 (237.52)	2285.10 (215.10)	1990.69 (293.56)
Land	0.75 (0.18)	1.71 (0.41)	3.12 (0.50)	1.69 (0.90)
Labor	22.68 (5.95)	23.16 (3.83)	24.34 (4.03)	23.24 (4.63)
Fertilizer	108.95 (35.03)	127.48 (29.01)	140.59 (34.29)	124.38 (33.82)
Seed	30.60 (7.73)	31.26 (6.96)	33.76 (7.66)	31.54 (7.27)
Age	44.11 (11.49)	46.70 (9.90)	51.88 (9.27)	46.91 (10.61)
Gender	0.57 (0.49)	0.71 (0.45)	0.82 (0.38)	0.69 (0.46)
Education	4.55 (2.17)	5.74 (2.01)	7.98 (2.87)	5.81 (2.53)
Household size	6.03 (1.70)	6.76 (1.48)	7.47 (1.55)	6.68 (1.64)
Coop. membership	0.36 (0.48)	0.53 (0.49)	0.62 (0.48)	0.50 (0.50)
Extension	26.05	31.42	36.81	30.83

	(6.71)	(7.28)	(6.40)	(7.88)
Land tenure	0.45	0.50	0.60	0.51
	(0.50)	(0.50)	(0.49)	(0.50)
Credit access	0.45	0.49	0.55	0.49
	(0.50)	(0.50)	(0.50)	(0.50)
Off-farm income	0.31	0.40	0.42	0.37
	(0.46)	(0.49)	(0.49)	(0.48)
Slope	0.68	0.46	0.30	0.50
	(0.46)	(0.50)	(0.46)	(0.50)
Livestock	0.60	1.37	2.56	1.37
	(0.63)	(0.92)	(1.20)	(1.13)

Note: standard deviations are given in parentheses.

5. Results and Discussion

Table 3 presents parameter estimates of the production frontier and inefficiency effect functions of the conventional SF and ZISF models. Table 3 also reports the results of the model diagnostics. The PLR test result is statistically significant at the 1% level, implying the presence of both inefficient and fully efficient farms in our sample. Additionally, the probability of being fully efficient is 12.1% and statistically significant at the 1% level. Results of maximum likelihood estimates of the coefficients for the stochastic production function indicate that the parameters for all input variables are statistically significant, and the signs of all input coefficients are positive, as expected, for both the conventional SF and ZISF models (see Table 3).

Table 3. Maximum likelihood estimates of the conventional SF and ZISF models.

Variable	Parameter	Conventional SF model		ZISF model	
		Coefficient	Std. error	Coefficient	Std. error
Production frontier function					
Constant	β_0	5.579**	0.091	5.682**	1.124

lnLand	β_1	0.175**	0.021	0.178***	0.019
lnLabor	β_2	0.159**	0.046	0.164*	0.048
lnFertilizer	β_3	0.306***	0.143	0.311***	0.137
lnSeed	β_4	0.235***	0.115	0.228**	0.126
Inefficiency effect function					
Constant	δ_0	-2.437***	0.085	-2.513***	0.114
Age	δ_1	0.003	0.012	0.002	0.011
Gender	δ_2	-0.731**	0.222	0.662	0.346
Education	δ_3	-0.234***	0.065	-0.301***	0.073
Household size	δ_4	-0.040	0.056	0.053	0.019
Coop. membership	δ_5	-0.148**	0.324	-0.170***	0.306
Extension services	δ_6	-0.031**	0.027	-0.035***	0.021
Access to credit	δ_7	-0.276*	0.021	-0.264*	0.033
Off-farm income	δ_8	-0.134	0.115	-0.149*	0.099
Land tenure	δ_9	-0.288**	0.106	-0.313**	0.087
Slope	δ_{10}	0.592	0.073	0.706	0.085
Livestock ownership	δ_{11}	-0.710***	0.089	-0.652***	0.078
Model diagnostics					
Probability	p	–		0.121***	0.064
Sigma-u	σ_u	0.124***		0.119***	0.008
Sigma-v	σ_v	0.087***		0.083***	0.012
Variance	σ^2	0.023***	0.004	0.021***	
Lambda	λ	1.425***		1.434**	
Gamma	γ	0.670	0.028	0.673	
PLR test		–		12.612***	
Log-likelihood		-114.523		-122.306	
Total number of observation		351		351	

Notes: ***, **, * indicate levels of significance at 1%, 5%, and 10%, respectively. A negative coefficient sign for variables of the technical inefficiency effect function implies that the variable has a positive effect on TE and vice versa.

5.1. Partial production elasticities and returns to scale

In our empirical analysis, we estimate partial production elasticities to assess the responsiveness of maize yields to varying levels of each of the classical inputs, ceteris paribus. The estimated coefficients of the Cobb-Douglas production function are directly read as partial production elasticities for the inputs (Coelli et al. 1998). The results listed in Table 3 indicate that maize yields are more responsive to fertilizer inputs than to other production inputs (i.e., seeds, land, and labor). In the ZISF model, the partial production elasticity value of 0.311 calculated for fertilizer input implies that a 1% increase in fertilizer use per hectare would increase maize yields by approximately 0.31%, ceteris paribus. The strong influence of fertilizer input observed is not surprising due to the benefits of using fertilizer to enhance crop yields (Hurley et al. 2018) and corroborates the findings of Anang et al. (2017), Zhuo and Shunfeng (2008), and Makombe et al. (2017). Furthermore, the corresponding estimates of partial production elasticities for seeds, land, and labor are 0.228, 0.178, and 0.164, respectively.

The study considers the estimation of returns to scale (also referred to as the elasticity of scale), which evaluates the proportional change in output that results from a unit proportional change in all inputs combined (Coelli et al. 1998). The elasticity of scale, which is computed by summing the partial production elasticities, is equal to 0.881. This result suggests that maize farms operate under decreasing returns to scale, implying that a 1% increase in all inputs can result in a less than 1% increase in output.

5.2. Determinants of technical efficiency

Table 3 provides the coefficient estimates of factors affecting technical inefficiency. We analyzed socioeconomic, institutional, and farm-specific variables. The results of the ZISF model indicate

that seven variables, including education, cooperative membership, extension services, access to credit, off-farm income, land tenure, and livestock ownership, are statistically significant. The negative sign of the coefficient of variables for the technical inefficiency effect function suggests that the variable has a positive effect on TE, and the reverse is correct for the positive sign of the coefficient.

Education appears to be positively associated with TE, as expected. Gebremedhin et al. (2009) also found that education has a significantly positive effect in improving the TE of smallholder farmers in Ethiopia. As a plausible explanation for this finding, better educated farmers are likely to have better access to necessary information on the state of agricultural technologies and on the optimal use of farming practices than their counterparts (Liu et al. 2017). Access to agricultural extension services also appears to have a significantly positive influence on TE. This finding is consistent with the work of Binam et al. (2004) and Ngango and Kim (2019). Indeed, the delivery of agricultural extension services is expected to encourage farm operators to learn and adopt better farming practices (Theriault and Serra 2014). The coefficient of access to credit is negative and statistically significant at the 1% level, implying that access to credit enhances the level of TE. Binam et al. (2004) also noted that smallholder farmers in the slash and burn agriculture zone of Cameroon with access to credit are more technically efficient than their counterparts without access to credit. Moreover, the negative and statistically significant coefficient of the land tenure variable suggests that land ownership is positively associated with TE. Livestock ownership is found to have a statistically significant and positive effect on TE. As expected, cooperative membership is also positively associated with TE. The negative and statistically significant coefficient of off-farm income suggests that farmers with off-farm income tend to exhibit higher levels of TE.

5.3. Technical efficiency estimates

The summary statistics of TE estimates for the full sample and for the three farm size groups are reported in Table 4. The average TE score for all households in the sample is estimated at 0.64. As we have estimated the output-oriented TE, the mean TE score of 0.64 implies that the maize output can be improved by approximately 36% without increasing the proportion of farm inputs used. This finding is comparable to those of previous studies that have attempted to analyze the TE of the agricultural production sector in Africa. For instance, Julien et al. (2019) applied the random parameter stochastic production frontier model to assess farm performance in Uganda and found a mean TE level of 0.64. Khataza et al. (2019) also report a mean TE of 0.60 for a sample of maize producers in Malawi.

Results for the relationship between farm size and TE are also presented in Table 4. The results indicate that on average, large-scale farms appear to be more technically efficient than both medium- and small-scale farms. Indeed, the average TE score for large-scale farms is 79.7% while the average TE scores for medium- and small-scale farms are 65.1% and 47.6%, respectively. These results denote a positive relationship between farm size and TE in Rwanda's maize production sector.

Table 4. Mean technical efficiency scores across farm size categories obtained from the ZISF model.

Range of TE (%)	Mean TE	Std. Dev.	Min	Max
Small-scale farms	0.476	0.045	0.213	0.706
Medium-scale farms	0.651	0.034	0.281	0.852
Large-scale farms	0.797	0.022	0.337	0.984

All farms	0.642	0.039	0.213	0.984

6. Conclusions and policy implications

In this study, we assessed the relationship between farm size and technical efficiency for the maize production sector in Rwanda. In addition, we analyzed potential determinants of technical efficiency for maize production systems in Rwanda. We employed the ZISF model for analytical purposes and a cross-sectional dataset consisting of a sample of 351 household farmers operating in the Eastern Province of Rwanda. The ZISF model is more advantageous than the conventional SF model due to its ability to account for both inefficiency and full efficiency in a sample.

Our empirical results reveal that all key production inputs, i.e., fertilizer, labor, seeds, and land, are statistically significant and have a positive effect on maize output. In particular, we found that maize output is more responsive to fertilizer input than to other production inputs (i.e., seeds, land, and labor). In terms of determinants of technical inefficiency, we found that education, cooperative membership, extension services, access to credit, off-farm income, land tenure, and livestock ownership have a significant and positive effect on TE. Furthermore, the average TE of maize farms in our sample is estimated at 0.64, denoting that maize output can be improved by approximately 36% without increasing the proportion of farm inputs used. With respect to the relationship between farm size and TE, we find that on average, large-scale farms appear to be more technically efficient than both medium- and small-scale farms. Hence, this study provides evidence of a positive relationship between farm size and TE for maize production in Rwanda.

From a policy perspective, given our study finding that large-scale farms appear to be more technically efficient than both medium- and small-scale farms, land reforms such as land

consolidation should be encouraged to enhance aggregate production growth (Key 2019). The government and partners should devise initiatives and incentives for small-scale farmers to gradually leave the farming sector in rural area and join off-farm activities because small-scale farmers appear to be less technically efficient than large-scale farmers. In addition, efforts targeting enhanced efficiency and productivity might focus on improving rural financial services to help farmers obtain loans needed for their agricultural investments. Agricultural extension services might also be improved in terms of quality and accessibility to all farmers. Farmers must also be granted greater access to intensive agricultural resources such as inorganic fertilizers and improved seed varieties. In this regard, the input subsidy policy initiated by the Rwandan government is expected to play a significant role. Finally, our study suggests that future research should explore the effects of land and labor market imperfections on efficiency and productivity in the Rwandan agricultural production sector.

Abbreviations

SSA: Sub-Saharan Africa; **TE**: Technical efficiency; **TFP**: Total factor productivity; **OLS**: Ordinary least squares; **SF**: Stochastic frontier; **DEA**: Data envelopment analysis; **MINAGRI**: Ministry of Agriculture and Animal Resources; **Kg**: Kilograms; **Ha**: Hectares; **TLU**: Tropical livestock units; **ZISF**: zero inefficiency stochastic frontier; **PLR**: pseudo-likelihood ratio

Declarations

Availability of data and materials

Data used for this study will be made available from the corresponding author up on request.

Competing interests

We declare that this research study has no potential competing interests.

Acknowledgements

This study is a part of the Doctoral thesis by the first author. We thank the government of the Republic of Korea through the Korean Government Scholarship Program (KGSP) for sponsoring this PhD program. We would like also to thank Papias Mucyo and Claude Migambi of the Rwanda Agriculture Board for their assistance with data collection.

Authors' contributions

JN conceived the idea for this research and was responsible for designing the study and data collection. JN was responsible for data analysis and original draft preparation. SH supervised, provided technical advice in formulation of the research objectives, and reviewed the manuscript. All authors read and approved the final manuscript.

Funding

No funding was received for this research study.

Ethics approval and consent to participate

Not applicable since the study involved maize crop.

Consent for publication

Not applicable.

References

Abdul-Rahaman, A., & Abdulai, A. (2018). Do farmer groups impact on farm yield and efficiency of smallholder farmers? Evidence from rice farmers in northern Ghana. *Food Policy, 81*, 95–105, doi:10.1016/j.foodpol.2018.10.007.

Abdulai, A. N., & Abdulai, A. (2016). Allocative and scale efficiency among maize farmers in Zambia: a zero efficiency stochastic frontier approach. *Applied Economics, 48*(55), 5364-5378, doi:10.1080/00036846.2016.1176120.

Ali, D. A., & Deininger, K. (2015). Is there a farm size-productivity relationship in African agriculture? Evidence from Rwanda. *Land Economics, 91*(2), 317–343, doi:10.3368/le.91.2.317.

Ali, D. A., Deininger, K., & Ronchi, L. (2015). *Costs and benefits of land fragmentation: evidence from Rwanda*: The World Bank.

Anang, B. T., Bäckman, S., & Rezitis, A. (2017). Production technology and technical efficiency: irrigated and rain-fed rice farms in northern Ghana. *Eurasian Economic Review, 7*(1), 95–113, doi:10.1007/s40822-016-0060-y.

Ansoms, A., Verdoodt, A., & Van Ranst, E. (2008). The inverse relationship between farm size and productivity in rural Rwanda. Universiteit Antwerpen, Institute of Development Policy (IOB).

Bambio, Y., & Bouayad Agha, S. (2018). Land tenure security and investment: Does strength of land right really matter in rural Burkina Faso? *World Development, 111*, 130–147, doi:10.1016/j.worlddev.2018.06.026.

Barrett, C. B., Bellemare, M. F., & Hou, J. Y. (2010). Reconsidering Conventional Explanations of the Inverse Productivity-Size Relationship. *World Development, 38*(1), 88–97, doi:10.1016/j.worlddev.2009.06.002.

Binam, J. N., Tonye, J., Nyambi, G., & Akoa, M. (2004). Factors affecting the technical efficiency among smallholder farmers in the slash and burn agriculture zone of Cameroon. *Food Policy, 29*(5), 531–545, doi:10.1016/j.foodpol.2004.07.013.

Bizoza, A. R. (2014). Institutions and the adoption of technologies: Bench Terraces in Rwanda. In *In: Vanlauwe B., van Asten P., Blomme G. (eds) Challenges and Opportunities for Agricultural Intensification of the Humid Highland Systems of Sub-Saharan Africa. Springer, Cham* (pp. 335–354): Springer.

Byiringiro, F., & Reardon, T. (1996). Farm productivity in Rwanda: effects of farm size, erosion, and soil conservation investments. *Agricultural Economics, 15*(2), 127–136, doi:10.1016/S0169-5150(96)01201-7.

Coelli, T., Rao, P. D., & Battese, G. E. (1998). *An introduction to efficiency and productivity analysis*: Kluwer Academic Publishers.

Desiere, S., & Jolliffe, D. (2018). Land productivity and plot size: Is measurement error driving the inverse relationship? *Journal of Development Economics, 130*, 84–98, doi:10.1016/j.jdeveco.2017.10.002.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society. Series A (General), 120*(3), 253–290, doi:10.2307/2343100.

Gautam, M., & Ahmed, M. (2019). Too small to be beautiful? The farm size and productivity relationship in Bangladesh. *Food Policy, 84*, 165–175, doi:10.1016/j.foodpol.2018.03.013.

Gebremedhin, B., Jaleta, M., & Hoekstra, D. (2009). Smallholders, institutional services, and commercial transformation in Ethiopia. *Agricultural Economics, 40*(s1), 773–787, doi:10.1111/j.1574-0862.2009.00414.x.

Helfand, S. M., & Levine, E. S. (2004). Farm size and the determinants of productive efficiency in the Brazilian Center-West. *Agricultural Economics, 31*(2–3), 241–249, doi:10.1111/j.1574-0862.2004.tb00261.x.

Holden, S. T., & Otsuka, K. (2014). The roles of land tenure reforms and land markets in the context of population growth and land use intensification in Africa. *Food Policy, 48*, 88–97, doi:10.1016/j.foodpol.2014.03.005.

Hurley, T., Koo, J., & Tesfaye, K. (2018). Weather risk: How does it change the yield benefits of nitrogen fertilizer and improved maize varieties in Sub-Saharan Africa? *Agricultural Economics, 49*(6), 711–723, doi:10.1111/agec.12454.

Jondrow, J., Lovell, C. A. K., Materov, I. S., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of econometrics, 19*(2–3), 233–238, doi:10.1016/0304-4076(82)90004-5.

Julien, J. C., Bravo-Ureta, B. E., & Rada, N. E. (2019). Assessing farm performance by size in Malawi, Tanzania, and Uganda. *Food Policy, 84*, 153–164, doi:10.1016/j.foodpol.2018.03.016.

Key, N. (2019). Farm size and productivity growth in the United States Corn Belt. *Food Policy, 84*, 186–195, doi:10.1016/j.foodpol.2018.03.017.

Khataza, R. R. B., Hailu, A., Doole, G. J., Kragt, M. E., & Alene, A. D. (2019). Examining the relationship between farm size and productive efficiency: A Bayesian directional distance function approach. *Agricultural Economics, 50*(2), 237–246, doi:10.1111/agec.12480.

Khataza, R. R. B., Hailu, A., Kragt, M. E., & Doole, G. J. (2017). Estimating shadow price for symbiotic nitrogen and technical efficiency for legume-based conservation agriculture in Malawi. *Australian Journal of Agricultural and Resource Economics, 61*(3), 462–480, doi:10.1111/1467-8489.12212.

Kimhi, A. (2006). Plot size and maize productivity in Zambia: is there an inverse relationship? *Agricultural Economics, 35*(1), 1–9, doi:10.1111/j.1574-0862.2006.00133.x.

Kumbhakar, S. C., Parmeter, C. F., & Tsionas, E. G. (2013). A zero inefficiency stochastic frontier model. *Journal of econometrics, 172*(1), 66-76, doi:10.1016/j.jeconom.2012.08.021.

Liu, J., Rahman, S., Sriboonchitta, S., & Wiboonpongse, A. (2017). Enhancing productivity and resource conservation by eliminating inefficiency of thai rice farmers: A zero inefficiency stochastic frontier approach. *Sustainability, 9*(5), 770–770, doi:10.3390/su9050770.

Makombe, G., Namara, R. E., Awulachew, S. B., Hagos, F., Ayana, M., & Kanjere, M. (2017). An analysis of the productivity and technical efficiency of smallholder irrigation in Ethiopia. *Water SA, 43*(1), 48–57, doi:10.4314/wsa.v43i1.08.

Mar, S., Nomura, H., Takahashi, Y., Ogata, K., & Yabe, M. (2018). Impact of erratic rainfall from climate change on pulse production efficiency in Lower Myanmar. *Sustainability, 10*(2), 402, doi:10.3390/su10020402.

Minagri (2018). Strategic Plan for the Transformation of Agriculture in Rwanda – Phase IV: 2018-2024. Ministry of Agriculture and Animal Resources (MINAGRI), Kigali, Rwanda.

Muchomba, F. M. (2017). Women's Land Tenure Security and Household Human Capital: Evidence from Ethiopia's Land Certification. *World Development, 98*, 310–324, doi:10.1016/j.worlddev.2017.04.034.

Musahara, H. (2006). Improving tenure security for the rural poor: Rwanda—Country Case Study. *LEP Working Paper #7. Food and Agriculture Organization of the United Nations*.

Musahara, H., & Huggins, C. (2005). Land reform, land scarcity and post-conflict reconstruction: A case study of Rwanda. *In: Huggins, C., Clover, J. (Eds.), From the ground up: Land rights, conflict and peace in sub-Saharan Africa. African centre for technology studies and institute for security studies, Nairobi and Pretoria*, 269–346.

Muyanga, M., & Jayne, T. S. (2019). Revisiting the Farm Size-Productivity Relationship Based on a Relatively Wide Range of Farm Sizes: Evidence from Kenya. *American Journal of Agricultural Economics, 101*(4), 1140–1163, doi:10.1093/ajae/aaz003.

Mwalupaso, G. E., Wang, S., Rahman, S., Alavo, E. J. P., & Tian, X. (2019). Agricultural informatization and technical efficiency in maize production in Zambia. *Sustainability, 11*(8), 2451, doi:10.3390/su11082451.

Ngango, J., & Kim, G. S. (2019). Assessment of Technical Efficiency and Its Potential Determinants among Small-Scale Coffee Farmers in Rwanda. *Agriculture, 9*(7), 161, doi:10.3390/agriculture9070161.

Ntihinyurwa, P. D., de Vries, W. T., Chigbu, U. E., & Dukwiyimpuhwe, P. A. (2019). The positive impacts of farm land fragmentation in Rwanda. *Land Use Policy, 81*, 565–581, doi:10.1016/j.landusepol.2018.11.005.

Place, F. (2009). Land Tenure and Agricultural Productivity in Africa: A Comparative Analysis of the Economics Literature and Recent Policy Strategies and Reforms. *World Development, 37*(8), 1326–1336, doi:10.1016/j.worlddev.2008.08.020.

Pritchard, M. F. (2013). Land, power and peace: Tenure formalization, agricultural reform, and livelihood insecurity in rural Rwanda. *Land Use Policy, 30*(1), 186–196, doi:10.1016/j.landusepol.2012.03.012.

Rada, N. E., & Fuglie, K. O. (2019). New perspectives on farm size and productivity. *Food Policy, 84*, 147–152, doi:10.1016/j.foodpol.2018.03.015.

Theriault, V., & Serra, R. (2014). Institutional environment and technical efficiency: A stochastic frontier analysis of cotton producers in West Africa. *Journal of Agricultural Economics, 65*(2), 383–405, doi:10.1111/1477-9552.12049.

Tran, T. Q., & Vu, H. V. (2019). Land fragmentation and household income: First evidence from rural Vietnam. *Land Use Policy, 89*, 104247–104247, doi:10.1016/j.landusepol.2019.104247.

World, B. (2018). World Development Indicators.

Xin, X., Zhang, Y., Wang, J., & Nuetah, J. A. (2016). Effects of Farm Size on Technical Efficiency in China's Broiler Sector: A Stochastic Meta-Frontier Approach. *Canadian Journal of Agricultural Economics, 64*(3), 493–516, doi:10.1111/cjag.12093.

Zeweld, W., Huylenbroeck, G. V., Hidgot, A., Chandrakanth, M. G., & Speelman, S. (2015). Adoption of Small-Scale Irrigation and Its Livelihood Impacts in Northern Ethiopia. *Irrigation and Drainage, 64*(5), 655–668, doi:10.1002/ird.1938.

Zhong, M., Zhu, Y., Chen, Q., Liu, T., & Cai, Q. (2019). Does household engagement in concurrent business affect the farm size-technical efficiency relationship in grain production?: Evidence from Northern China. *China Agricultural Economic Review, 11*(1), 125-142, doi:10.1108/CAER-11-2016-0179.

Zhuo, C., & Shunfeng, S. (2008). Efficiency and technology gap in China's agriculture: A regional meta-frontier analysis. *China Economic Review, 19*(2), 287-296, doi:10.1016/j.chieco.2007.03.001.