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Profit efficiency among kenyan maize farmers

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ABSTRACT

The profit efficiency (PE) of maize farming and its determinants are estimated using the true random effect (TRE) approach. A survey of maize farmers was conducted in Uasin Gishu, one of Kenya's top maize-producing regions. Clearly, maize farmers can increase their profits based on the mean PE of 0.62. In terms of profitability, maize farming is elastically affected by the price of maize, but inelastically affected by the price of inputs. In households where the head of household is male, household sizes are larger, and farm sizes are larger, inefficiencies of profit are significantly reduced. Despite this, factors such as the distance between home and the maize farm, soil characteristics, maize diseases, along with natural disasters significantly increase profit inefficiency. According to the findings of the study, maize prices are more effective targets for developing supportive policies than input prices. To significantly increase PE, farmers would benefit from programs designed to improve their production and management skills to preserve soil health and minimize damage caused by disease and natural disasters. Furthermore, increase in PE would be achieved by improving farm size through land-use policies.

1. Introduction

The majority of Kenyan households rely on maize for the majority of their calories and earnings. The source of nearly 70 % of cereal calories in daily diet is maize, which provides over 30 % of the calories. Additionally, maize is consumed by 85 % of the population, confirming its universality throughout the country [1]. Kenyan maize accounts for 3 % of the gross domestic product (GDP) and 12 % of the agricultural GDP. Furthermore, various studies estimate that maize contributes 20 % to agricultural production and 25 % to employment [2,3]. Furthermore, it contributes 36 % of calories, 72 % of starch, 10 % of protein, and 4 % of fat. Furthermore, it supplies 365 kcal per 100 g of energy [4,5]. Thus, maize is a key indicator of food security in the country.

In Kenya, over 80% of maize comes from smallholder farmers with limited resources to improve productivity, which leads to low yields [6,7]. Maize production in Kenya is low due to low yields, which results in low outputs that fail to meet demand. Farmers are expected to see higher maize prices as a result of this, under normal circumstances. Maize prices in Kenya, however, remain low due to resource poverty and the inability of farmers to store their produce until better prices become available [8,9]. Thus, farmers are not able to maximize return on investment for maize production. As a result of low returns for farmers, maize production becomes unattractive, causing them to cut back on production in an effort to survive, as a result, the demand gap for maize, particularly for domestic consumption, becomes more pronounced [10]. Maize is Kenya's primary food source, so a shortage of maize would result in food insecurity and prevent Kenya from reaching the poverty-reduction and hunger-reduction Sustainable Development Goals (SDGs) [11]. Therefore, it is necessary to ask, alongside an increase in prices, what other strategies can be used to increase profits and efficiency for resource poor maize farmers in order to transform the maize industry into a job-creating industry, and that is why this study

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examined the profitability efficiency of Kenyan maize farmers.

Increasing profitability of Kenya's smallholder farmers, whose production contributes more than 80% of its agricultural production, requires efficient use of their resources [12,13]. Policies can benefit from profit efficiency estimates as they provide more information than other efficiency measures. Due to the fact that agriculture in Kenya is the primary sector, it is important to consider the profitability of farms when implementing development strategies. It is essential for farmers to realize their potential and establish the appropriate mechanisms in order to increase profit efficiency levels by understanding how profitability efficiency levels are correlated with the characteristics of the farmer and farm. Agricultural smallholders growing maize are expected to benefit from this study by learning how to maximize their profit while reducing costs, which will lead to the development of Kenya's maize subsector and the creation of jobs for the unemployed. This will result in the reduction of poverty and the elimination of hunger, thereby fulfilling sustainable development goals 1 and 2. The aim of this study is to determine how profitable maize farming is and to analyze factors affecting inefficiency using a true random effect model.

Kenya must import maize to meet its total maize demand due to persistent supply shortages [14]. A low growth in maize productivity has contributed to Kenya's maize deficits (around 2 %, versus 3.5 % for growth in the population) [8,15]. In Kenya, four million people are normally in need of food assistance on a yearly basis (consuming 114 kg of maize on average per person annually), according to a government report [3]. For food security, maize imports need to be reduced (or eliminated) by increasing maize productivity, a 157 % increase in maize yield would be sufficient for maize productivity to be sufficient [16]. Unfortunately, the country's maize productivity has declined over the years. Maize grain yields have hovered between 1.4 and 1.8 $Mgha^{-1}$ over the past decade (2012–2021) [16]. Most of Kenya's staple food comes from smallholders, but they have difficulty in assessing investment capital, knowledge, in addition to agricultural inputs. Therefore, small-scale farms in Kenya produce only about 1 $Mgha^{-1}$ of maize, which is lower than the country-wide average and considerably lower than the yield of 6–8 $Mgha^{-1}$ that can be achieved with recommended management practices [17]. A significant portion of the gap in crop yield can be attributed to inefficient resource use or allocation.

For smallholder farmers to remain profitable, they must be efficient, generating the highest profit possible even under the conditions of a fixed cost of production and price. An economically rational combination of inputs and outputs is necessary for farmers to be profitable. The right proportions and quality of inputs are crucial to maximizing productivity by utilizing the resources efficiently [18,19]. The efficiency of maize production has received a great deal of attention in recent decades. Profit efficiency analysis (PE), which is a broad concept, has attracted less attention from agricultural economists than technical efficiency estimation, despite its potential to guide policymakers on how to increase production through price tools, in particular when input and output market prices influence maize farmers' production decisions. According to Refs. [17–19], it is only appropriate to measure efficiency in technical or cost terms when a firm's objective is to maximize output or minimize input (cost), not profit. As a result, considering profit frontier functions would be more advantageous, for example, in maize farming in Western Kenya, where input and output prices are largely determined by market prices.

There have been several studies estimating maize profit efficiency and inefficiencies in Bangladesh [20], Ghana [21], South Africa [19], Nigeria [22] and Ghana [23,24]. However, none of the studies have considered individual farm characteristics (heterogeneity), the operational form of production functions, or inefficiency errors' distribution. As a result, profit frontier parameters and related PE scores could be biased. In this first study of PE estimation in maize production, it examines the effects of heterogeneity within farms, functional models used in production functions, and inefficiency (one-sided error) distributions according to alternative specifications. Taking into account the conclusions of [25] introduction of TRE, the stochastic frontier model (SF) and an inefficiency model, which are both dependent on farm heterogeneity, are simultaneously estimated. In this study, farm heterogeneity is examined by the estimation and comparing maximum likelihood estimation (MLE) for a pooled model and maximum simulated likelihood estimation (MSLE) for a TRE model. Taking advantage of well-established functional forms (for example, Translog and Cobb-Douglas) and for the assessment of model efficacy, assumptions about the distribution of inefficiency errors (half-normal, exponential, and truncated normal) were made, as well as log-likelihood ratios and Akaike information criterion (AIC) and Bayesian information criterion (BIC). This study will provide valuable information necessary to develop policies that will support maize farmers in Kenya, one of the largest maize producers in East Africa, thereby serving as a valuable resource to maize farmers everywhere.

2. Literature review

To estimate profit efficiency in maize farming in Kenya and to analyze its determinants, stochastic frontier analysis (SFA) is used. As a parametric technique, SFA was developed by Ref. [26], using a production function, it is possible to calculate the difference between observed and potential outputs. In addition to separating noise and inefficiencies, SFA also identifies their sources, which makes it preferable to the comparable non-parametric technique called Data Envelopment Analysis (DEA). Even though non-parametric methods have increased in popularity for modeling stochastic variability, discussed in Ref. [27] and subsequently used in Ref. [28], the DEA cannot simultaneously take into consideration efficiency and the variables that affect it. SFA, however, employs the likelihood estimator to simultaneously examine profit efficiency effects as well as well as the factors that determine it. Furthermore, it allows for direct assumptions to be imposed on economic theory, for example profit maximization, which is crucial for this analysis.

In modeling profit efficiency among smallholder maize farmers, there are several methodological caveats that require attention. A first consideration of DEA is that it does not require a specific form of the production function or distributional assumptions to be made for the inefficiency error term [29]. Non-parametric approaches are limited by an inherent limitation: statistical noise can inflate inefficiency scores if the data are contaminated. SFA separates statistical noise from the inefficiency term; however, it requires that SF functions and one-sided error terms have prior production functional forms [30]. One of the major limitations of the SF approach is the absence of a priori reasoning for the selection of the distributional and production functions for the SF functions, as well as the one-sided error terms, according to Refs. [31,32]. A thorough review of techniques and concepts for estimating efficiency of production has taken place over the last few decades [33–35]. Cobb-Douglas (CD) production function is used commonly in empirical parametric studies [36,37] as well as flexible translog (TL) production functions [30,38]. TL is a generalized form of CD, and *LR* is used to compare the two for specific datasets [37,39]. develop a selection criteria and choice set of production functional forms that are relevant to production. In general, half-normal distributions [40,41], exponential distributions [42,43], truncated normal distributions [44,45], and gamma distributions [43,46] are used for estimating one-sided error terms. According to Ref. [47], the selected inefficiency error term's distribution form affects inefficiency estimates. For mitigation of biases and assessing whether selection estimates are robust across functional and distributional forms, this study used two functional models (CD and TL); a half-normal, exponential, and truncated normal distributional specification was used to define the inefficiency term.

A two-step approach or a one-step approach should also be chosen when computing smallholder farmer efficiency levels. With the one-step method, efficiency frontier models and inefficiency determinants models are both estimated in a single step by maximizing a joint likelihood function, while with the two-step method, efficiency estimates from the first step are regressed on potential explanatory variables in the second step. The two-step method involves regressing efficiency estimates from the first step on potential explanatory variables in the second step. Two-step estimation has been shown to be problematic by Refs. [46,48]: (i) due to the strong correlation between the input variables and the variables used to explain inefficiency, parameter estimates will be biased in the SF model; (ii) the inefficiency term's explanatory variables are underestimated; and (iii) the inefficiency explanatory variables are tested for statistical significance in a non-standard manner. A single step method for estimating the frontier and inefficiency models is described by Refs. [46,47].

Agricultural economics has widely used profit efficiency (PE) measurement techniques [18,20,23,49–52], but there are few applications in maize farming. Based on the translog stochastic frontier model, Wongnaa et al. (2019) evaluated the profitability of Ghanaian maize farmers. As a result, Ghanaian maize production has proven to be profitable, but a rise in the price of pesticides, fertilizers, herbicides, labour, or seeds would adversely impact profitability. By using a SF profit function [51] to calculate the PE of cocoa production in Ghana with a TL. According to estimates, PE was 89.9 % and PE was positively impacted by males, manual pollination, cocoa tree age, and accessibility to technology, whereas farming experience negatively affected PE.

In northern Uganda, a study by Ref. [49] examined smallholder rice farmers' PE, marketing model distribution, and inefficiency sources. Using Maximum Likelihood Estimation techniques, a one-step model of stochastic profit frontiers was utilized to predict the PE and the sources of inefficiency of smallholder rice farmers. Results indicated a mean PE level of 59 %. For certified groundnut seed production (CG) and conventional groundnut production (CG), 53] employs a metafrontier model with two steps to estimate PE and the factors affecting it in Northern Ghana. Compared to CG production, CGS production was found to be more profitable and profit-efficient. A stochastic frontier profit function is used to examine how farm size affects profitability in pangas pond fish farming in Bangladesh by Ref. [18]. Based on the findings, profit efficiency averages 74 %, translating into 26 % of profit loss due to technical and allocative inefficiencies.

In Ghana's intensive housing system of layer production [52], analyses PE and its drivers using translog normalized profit frontiers. Results indicate that feed costs and labour costs negatively affect layer producers' profits, while all input variables positively affect layer output. The profitability of layer producers is about 54 % and their returns to scale are increasing [20]. used the profit frontier model and the model that takes into account inefficiency effects to examine the PE and the causes of inefficiency among hybrid maize growers in Bangladesh. Furthermore, a PE score of 0.71 indicated that profit efficiency was 29 %. Individual heterogeneity was not taken into account in these empirical studies, nor were the proper error distributions and functional forms chosen. The TRE model introduced by Refs. [22a,22b] is used to model farm heterogeneity by accounting for farm effects and estimating frontier and inefficiency models simultaneously. Furthermore, the distribution of inefficiency error terms and the sensitivity of efficiency estimates were analyzed.

Geographical, farm, and farmer variables can explain variations in agricultural production inefficiencies. Literature reviews [12,13,49,53–61] and in the current study, the study site's reality guides the research. This study explains variation in profit inefficiencies among Kenyan smallholder maize farmers based on factors such as education, experience in maize farming, gender of household heads, the size of the household, the size of the farm, ownership of the land, training in the field, distance between the home and the field, salinity and alkalinity of the soil, disease of the maize crop, and climatic conditions. As part of this study, it was hypothesized that household heads' educational level, maize farming experience, male gender, household size, farm size, land ownership, and in-field training factors would reduce profit inefficiency, while distance between a homestead and a maize farm, soil quality, pests and diseases, and natural disaster factors will increase profit inefficiency.

3. Methodology

3.1. Stochastic profit frontier

Using fixed input levels and input prices [51], defined PE in maize farming as a farm's ability to maximize profits. Profit losses caused by failing to operate on the profit frontier are calculated as maize farming's profit inefficiency. Technical inefficiency, allocative inefficiency, and scale inefficiency can all translate into profit inefficiency [62]. There are two types of techniques commonly employed in estimation of PE: parametric and non-parametric. As part of this research, a parametric method is used to estimate the sources of inefficiency in maize farming. TRE [25,63], which can separate unobserved heterogeneity between farms from inefficiency, are used to separate unobserved inefficiency from unobserved heterogeneity. By identifying individual heterogeneity separately, SF parameters can be estimated unbiasedly and profit inefficiency scores can be calculated. Greene's TRE model's stochastic variable profit frontier function can be expressed as follows:

$$\pi_{it} = f(P_{it},\ K_{iit}, L_{it}, \beta_i) * exp(k_i + \nu_{it}) \tag{1}$$

In this model, $i = 1, 2, 3 \ldots.., n$ identify each farmer's maize farm; the subscripts $i = 1, 2, 3, \ldots.., T_i$ denote periods of time; $f(\bullet)$ in stochastic profit frontier functions, this is the deterministic component; π_{it} is profit which is derived by subtracting total variable costs from gross revenue as a whole; P_{it} identifies maize's price; K_{iit} represents input prices; L_{it} represents fixed inputs to guarantee short-run profits; the unknown parameters are represented by the vector β_i; the k_i represent the random unobserved farm heterogeneity in production; a composed error term is ε_{it} $(\varepsilon_{it} = \nu_{it} - u_{it})$; ν_{it} is a term representing random noise, characterized by a zero-mean distribution of identically independent distributions (iid) and variance of $\sigma^2(\nu \sim N(0, \sigma^2))$; and u_{it} accounts for profits inefficiency that vary with time based on the assumption that it has a distributed mean (u_{it}) and variance of $\sigma^2_{u_{it}}(u_{it} \sim N(u_{it}, \sigma^2_{u_{it}}))$.

Modelling profit inefficiency based on explanatory factors:

$$\mu_{it} = \delta_{it} + \delta S_{it} \tag{2}$$

where the vector S_{it} contains explanatory variables that explain variations of maize farmer profit inefficiency, while δ representing an unknown parameter vector.

According to the equation shown below, it is the ratio between actual profit and potential profit that is used to calculate the PE that varies over time $(\mathrm{PE_{it}})$ of the ith farmer's maize farm.

$$\begin{aligned} PE_{it} &= \pi_{it} / f(P_{it},\ K_{iit}, L_{it}, \beta_i) * exp(k_i + \nu_{it}) \\ &= f(P_{it},\ K_{iit}, L_{it}, \beta_i) * exp(k_i + \nu_{it} - u_{it}) / f(P_{it},\ K_{iit}, L_{it}, \beta_i) * exp(k_i + \nu_{it}) = exp(-u_{it}) \end{aligned} \tag{3}$$

Based on the approach of [61,62], for each observation, the farm-specific profit inefficiency (u_{it}) is calculated based on its conditional distribution and the composed error term ε_{it}. In the presence of a distribution of normality for ν_{it} and half-normality for u_{it}, an estimate of u_{it} given $\varepsilon_{it,}$ is computed using the following formula:

$$E(u_{it} / \varepsilon_{it}) = \sigma_* \left[f(\varepsilon_{it}\gamma/\sigma) / 1 - F(\varepsilon_{it}\gamma/\sigma) - (\varepsilon_{it}\gamma / \sigma) \right] \tag{4}$$

where $\varepsilon_{it} = \nu_{it} - u_{it},\ \gamma = \sigma_u/\sigma_\nu,\ \sigma = \sqrt{\sigma_u^2 + \sigma_\nu^2},\ \sigma_* = \sqrt{\sigma_u^2\sigma_\nu^2/\sigma^2}$, and the standard normal density function is represented by $f(\bullet)$, while the cumulative density function is represented by $F(\bullet)$. Maximum likelihood estimates of variance $(\sigma_u,\ \sigma_\nu)$ are obtained from equation (1).

PE_{it} values range from 0 to 1. Using given input and output prices, the farmer obtains maximum profit PE_{it} (or $u_{it} = 0$). When PE_{it} falls below one (or u_{it} exceeds 0), the farmer does not achieve optimal profitability (below the frontier).

3.2. Specifications of the model

A profit model specification incorporates linear homogeneity after normalizing input prices and variable profits by output prices. By demeaning these values, these values are then normalized. As a result of demeaning normalization, potential collinearities between values at the first order and the squared and interacting terms of those values are broken down. It also simplifies the estimation process by clarifying first-order coefficients between input and output variables, along with their significance levels and signs. First-order estimates can also be interpreted as partial profit elasticities computed from input costs and fixed inputs at the mean of the study sample. Maize farmers' translog (TL) profit frontier function with normalized stochasticity is as follows:

$$\begin{aligned} ln\ \pi_{it} = {} & \alpha_0 + \sum_{j=1}^{3} \alpha_j\ ln\ P_{jt} + \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3} \alpha_{jk}\ ln\ P_{jt}\ ln\ P_{kt} + \sum_{l=1}^{2} \beta_l ln\ Y_l + \frac{1}{2}\sum_{l=1}^{2}\sum_{m=1}^{2} \beta_{lm} ln\ Y_l ln\ Y_m + \sum_{j=1}^{3}\sum_{l=1}^{2} \delta_{lj}\ ln\ P_{jt} ln\ Y_l + \sum_{p}^{2} \vartheta_p D_p + w_i \\ & + \nu_{it} - u_{it} \end{aligned} \tag{5}$$

where the subscripts i and t are in accordance with what was previously defined; π_{it} is a measure of maize farming profitability (in US dollars) (gross revenue less varying costs) adjusted for output prices (P_y in US\$/kg); P_j $(j = 1, 2, 3)$ represents input prices such as seed (*PSD* in US dollars per kilo) fertilizer *PFR* in US dollars per kilo), and labour *PLB* in US dollars per kilo), and are normalized to the output price; Y_l $(l = 1, 2)$ are fixed input quantities, such as maize-planted area (*LAN* in hectares) and expenditures for preparing the land, seeding, applying herbicides, pesticides, and harvesting (*CAP* in US dollars); D_p are maize variety dummy variables (DHQM, 1 for high-quality maize varieties, 0 otherwise); farm heterogeneity is captured by w_i, which is a term representing random noise, characterized by *iid* with a mean of zero and variance of $\sigma^2_w(w_i \sim N(0, \sigma^2_w))$; υ_{it} and u_{it} both capture random noise and profit inefficiency, as defined in equation (1); and α β δ and ϑ are parameters that are not known and need to be computed

Based on the independent variables capturing the characteristics of the farmer and the farm, the logarithm variance of profit inefficiency term is modelled:

$$\log \sigma^2_{u_{it}} = \varrho_0 + \varrho_1 EDU_i + \varrho_2 \, EXP_i + \varrho_3 DGD_i + \varrho_4 HSZ_i + \varrho_5 FSZ_i + \varrho_6 LDO_i + \varrho_7 EXT_i + \varrho_8 DST_i + \varrho_9 DAL_i + \varrho_{10} DSA_i + \varrho_{11} DSE_i + \varrho_{12} DIS_i \quad (6)$$

in this case, *EDU* represents the household heads' education level (school years); *EXP* represents the maize farming experience of household heads (years); *DGD* indicates a household's head's gender; *HSZ* is the measurement of the size of maize farmers' households, which pertains to the number of family members within a household; *FSZ* represents the maize-cultivated area (hectares); *LDO* is the ratio of maize land owned by a household to total maize-cultivated area owned by the household (%); *EXT* refers to the number of field trainings that were attended; *DST* measures the distance between home and maize farm (km); *DAL* and *DSA* represent soil quality dummies, with 1 representing areas to alkalinity and those prone to salinity, respectively; *DSE* indicates the percentage of maize losses due to maize diseases reported by farmers; and *DIS* measures disasters caused by nature like flooding and drought that lead to maize losses. $\varrho_0 - \varrho_{12}$ are parameters not known that need to be computed.

It is initially necessary to run both TRE and Pooled models (that ignores panel structure and treats $\sigma_{w_i} = 0$) the one-sided error term is defined in equations (5) and (6) by alternative distributions such as half-normals, exponentials, and truncated normals. A Cobb-Douglas (CD) production function version is also estimated (which treats $\alpha_{jk} = \beta_{lm} = \delta_{lj} = 0$) and an appropriate functional form is selected using the LR test by testing the null hypothesis $H_0 : \alpha_{jk} = \beta_{lm} = \delta_{lj} = 0$, and in order to test the null hypothesis that farms do not have heterogeneity $(H_0 : \sigma_{w_i} = 0)$, the appropriate model has to be selected.

3.3. Variable definitions and data

In this study, data from a randomly selected sample of maize farmers in Uasin Gishu County, located in the west central region of Kenya, is collected from the farm level. For selecting respondents, a multiple-stage random sampling procedure was employed. There are 47 counties in Kenya, each of which has a constituency and a ward. In this sense, wards are the smallest electoral divisions in the country and are the closest to citizens in terms of government services. Each constituency's wards were randomly selected during the first stage. Based on the high level of maize production by subsistence farmers within each of the six constituencies in Uasin Gishu County, two wards from each constituency were selected at random. The study sample was constructed from maize farmers' information compiled from agricultural extension officers in the selected wards. To generate quantitative and qualitative results from this study, a statistically plausible sample of the target population is required. It is therefore crucial to ensure accurate sampling to minimize sampling bias and estimate the population's confidence level statistically.

For the final stages of the survey, 44–45 maize farmers above 18 years of age from each selected ward were interviewed face-to-face. Kenyan laws define anyone over 18 as an adult. A total of 532 respondents were generated because of this sampling procedure. In this study, 511 farmer responses were used after removing incomplete responses. Approximately 1021 farmer-season observations can be found in the final data set since each response might contain data from two cropping seasons in the 2020/21 production year. All farmers were informed they could withdraw from the interviews at any time and were required to provide consent to participate in them. As the high anticipated rate of illiteracy will prevent many from providing written consent, verbal consent was requested. It was

Table 1
Descriptive statistics and variable definitions.

Variable	Definition (Unit)	Mean	SD	Min	Manx
Frontier model					
π	Variable profit (US$/ha)	326	98.83	118.50	818.17
P_y	Maize price (US$/kg)	1.05	0.63	0.90	1.40
PSD	Seed price (US$/kg)	1.57	0.15	0.88	1.98
PFR	Fertilizer price (US$/kg)	52.17	14.42	41.16	59.66
PLB	Labour price (US$/man-day)	68.10	21.72	50.25	77.82
LAN	Area cultivated with maize (ha)	2.25	2.09	0.15	11.80
CAP	Fixed input expenditures (US$/man-day)	221.74	75.45	178.60	240.37
DHQM	1 for DHQM varieties, 0 otherwise	0.44	0.49	0	1
*DSN*1	For cropping season 1, 1; otherwise, 0	0.38	0.46	0	1
*DSN*2	For cropping season 2, 1; otherwise, 0	0.28	0.45	0	1
Inefficiency model					
EDU	Education level	7.33	4.21	0	15
EXP	Years of experience in maize farming	17.75	8.24	2	41
DGD	For males, 1; otherwise, 0	0.85	0.21	0	1
HSZ	Size of household	4.64	1.60	2	12
FSZ	Area cultivated with maize (ha)	2.25	2.09	0.15	11.80
LDO	Ownership of land (%)	73.76	26.09	0	100
EXT	Trainings on maize production attended	3.48	3.28	0	20
DST	Distance to the maize farm in kilometers	0.97	2.36	0	13
DAL	For areas prone to alkalinity, 1; otherwise, 0	0.18	0.23	0	1
DSA	Areas prone to salinity, 1; otherwise, 0	0.12	0.13	0	1
DSE	Disease of maize (%)	13.66	4.25	0	32
DIS	Disasters of nature (%)	20.72	10.83	0	60

Note: Exchange rate: 1US$ = ~KShs 115 in 2020/21.

noted that consent was given by the trained enumerators. In Table 1, descriptive statistics are presented.

As shown in Table 1, the first section provides definitions as well as statistical descriptions for frontier profit function variables, such as profit variable (π), prices of maize (P_y), cost of inputs (PSD, PFR, and PLB), and fixed input costs (LAN and CAP), as well as maize varieties ($DHQM$) and cropping seasons ($DSN1$ and $DSN2$) dummies. The profit variable (US dollars per kilo) is calculated by subtracting the total maize revenue from the total variable cost. As [64,65] pointed out, data observations with negative profits can be handled appropriately. The final estimates do not suffer from dropping observations that have negative variable profit, as there are only eleven such observations. It is estimated that maize farming produces about US$326.72 in variable profit per hectare, ranging between US$118.50 and US$818.17. In terms of output price (US$/kg), the average was US$1.05 per kilogram (range US $0.90–1.40/kg).

This study included a dummy variable of high quality maize variety in order to quantify the impact of high quality maize variety on the PE of maize production. Farmers in the study area adopted different varieties of maize. The varieties of maize were categorized as traditional and high-quality maize (HQM). Due to their high output prices and lower input costs, HQM varieties are promoted in Kenya as a means of increasing output quality and profits for maize farmers. According to descriptive statistics, HQM varieties are adopted at a low rate of 44 %, compared with 56 % for traditional varieties. In comparison to conventional maize varieties, the HQM dummy should indicate a positive result in terms of maize farming profits.

In the second part of Table 1, descriptive statistics are presented about farm and farmer characteristics. Despite having only 7.33 years of schooling, Kenyan maize farmers are highly experienced farmers, with 17.75 years of maize farming experience on average. A majority of maize farming households, 85 %, are headed by a male. A total of 3.48 maize production trainings are attended on average. Inefficiency in profit is regarded as having a negative relationship with these four variables. Households have an average size of 5 people.

Approximately 74 % of the cultivated land is owned by farmers, meaning that 26 % is rented. There is a significant variation in distance between households with maize farms, with a mean distance of 0.97 km among these households. It is hypothesized that household size and farm ownership are negatively correlated with profit inefficiency among farmers, and maize farm distance is hypothesized to positively impact it. In Table 1, 18 % and 12 % of farmers cultivate in areas with a high alkaline content and a high salinity content, respectively. Maize diseases and natural disasters have also been a problem in the Uasin Gishu maize farming area, resulting in average output losses of 14.66 and 20.72 %, respectively. A positive association is hypothesized between these four variables and profit inefficiency.

4. Results

4.1. Estimates of stochastic profit frontiers

A Pooled and TRE model was implemented using Stata (16) using Fé & Hofler (2020)'s "sfcross" and "sfpanel" packages. According to Table 2, the appropriate functional model and form were determined using the LR test. For the Pooled and TRE models, as well as for all distribution choices, both the CD and TL functional forms were tested using the LR statistics ($H_0 : \alpha_{jk} = \beta_{lm} = \delta_{lj} = 0$) are much higher (columns 4 and 7) than the critical value of $\chi^2_{0.99}(15) = 29.93$ [66]. TL is therefore preferred over CD functional form. In order to determine whether farms are heterogeneous ($H_0 : \sigma_{w_i} = 0$) a LR test is run using the pooled model against the TRE model, using the TL form. In all distributions of inefficiency error terms, LR statistics exceed the critical value $\chi^2_{0.99}(1) = 5.41$ for 99 % significance, confirming farm heterogeneity. MSLE method also supports farm heterogeneity by estimating parameter σ_{w_i} statistically significantly (Table 3), suggesting it is more appropriate to use the TRE model as opposed to the pooled model in this case.

The one-sided error term distributional forms for translog TRE models can be compared using AIC and BIC values. Best-fit models will have AIC and BIC values that are the lowest. The truncated normal distribution has the lowest AIC (−160.4) and BIC (19.13) compared to the half-normal (AIC = −159.3) and BIC = 24.28) and exponential distributions (AIC = −132.4) and BIC = 36.42). To achieve this, a truncated normal distribution would be more appropriate [67,68],supports these findings. Translog TRE model estimation using truncated normal distributions is discussed in this study. Table 3 presents the TRE and pooled parameters.

Both the Pooled and TRE models show statistically significant and positive parameter estimates for the DHQM. A highly statistically significant estimate of Theta (σ_{w_i}) is obtained for the TRE model, which captures unobserved farm heterogeneity. In the pooled and TRE models, LR test results indicate there is undetected time-invariant heterogeneity in farm characteristics present in our dataset.

For maize farmers' reactions to variations both in input prices and output prices, partial elasticities based on profit were estimated based on input prices, output prices, and fixed inputs. Policymakers will be able to use this information to design supportive policies for

Table 2
LR results for inefficient distributional forms, functional specifications, and SF specifications.

Distribution	Pooled			TRE			Model Selection
	CD	TL	LR	CD	TL	LR	LR
Half-normal	35.91	69.77	56.61	73.98	98.97	38.87	47.29
Exponential	37.12	69.89	54.43	78.28	107.95	48.22	65
Truncated	44.88	77.95	55.03	85.11	114.65	47.98	62.3

The critical value

Table 3
Inefficiency and variable profit frontier estimates.

Variable	Pooled		TRE	
	Coefficient	Standard Error	Coefficient	Standard Error
The frontier model				
Constant	0.369***	0.009	0.366***	0.01
lnPSD	−0.302***	0.02	−0.315***	0.022
lnPFR	−0.331***	0.04	−0.325***	0.045
lnPLB	−0.256***	0.016	−0.272***	0.021
lnLAN	0.914***	0.032	0.92***	0.037
lnCAP	−0.139	0.096	−0.141	0.112
$0.5\ln PSD^2$	−0.505***	0.13	−0.725***	0.137
lnPSD *PFR	0.076	0.136	0.01	0.137
lnPSD *PLB	0.043	0.08	−0.054	0.084
lnPSD *LAN	−0.107	0.096	−0.182	0.098
lnPSD *CAP	0.053	0.092	−0.067	0.092
$0.5\ln PFR^2$	−0.548	0.412	−1.045**	0.446
lnPFR *PLB	0.089	0.205	0.196	0.226
lnPFR *LAN	−0.611***	0.235	−1.008***	0.239
lnPFR *CAP	0.482**	0.231	0.664***	0.233
$0.5\ln PLB^2$	−0.424**	0.191	−0.522***	0.217
ln PLB *LAN	0.259*	0.135	0.237*	0.134
ln PLB *CAP	−0.256*	0.132	−0.412***	0.141
$0.5\ln LAN^2$	−0.007	0.22	−0.02	0.233
lnLAN*CAP	0.014*	0.205	−0.161	0.216
$0.5\ln CAP^2$	−0.135	0.201	−0.159	0.213
DHQM	0.016***	0.004	−0.083***	0.005
The inefficiency model				
Constant	−0.465**	0.223	−0.346***	0.249
EDU	−0.083	−0.06	−0.155	0.12
EXP	−0.017	0.041	−0.11	−0.069
DGD	−0.662***	0.232	−0.561**	0.228
HSZ	−0.095**	0.037	−0.074*	0.038
FSZ	−0.228***	0.053	−0.175***	0.047
LDO	−0.114***	0.043	−0.083*	0.044
EXT	−0.052	0.037	−0.087**	0.037
DIST	0.13***	0.038	0.115***	0.039
DAL	0.753***	0.143	0.571***	0.136
DSA	0.631***	0.216	0.467**	0.211
DSE	0.113***	0.034	0.181***	0.03
DIS	0.539***	0.067	0.388***	0.062
Model properties				
$E(\sigma_{u_{it}})$	0.425	–	0.439	–
$\sigma_{v_{it}}$	0.116***	0.006	0.079***	0.007
$\sigma^2_{v_{it}}$	–	–	–	–
σ_{w_i}	–	–	0.101***	0.007
logL	77.95		114.65	

Note: A significance level of 10, 5, or 1 % is indicated by an *, **, or ***.

maize farmers. As shown in Table 4, the models produce consistent results. In all theoretical cases, for input prices, partial profit elasticity is negative, but it is positive for output prices and fixed input prices. When it comes to output price, variable profit is elastic, but it is inelastic when it comes to input price. As far as maize price is concerned, the mean elasticity of 1.47 is slightly lower than the estimate of 1.82 reported by Ref. [23] and the estimate of 1.75 reported by Ref. [69].

Taking into account the mean elasticities for seed, fertilizer, and labour costs, a 10 % increase in each of these costs would decrease maize production's profitability by 1.9 %, 2.0 %, and 1.5 %, correspondingly. According to Refs. [20,21], these results are consistent.

Table 4
Variable inputs' profit elasticity in terms of input prices and fixed costs.

Variable	Pooled		TRE	
	Mean	S.D.	Mean	S.D.
Price of maize	1.45	0.24	1.47	0.17
Price of Seed	−0.18	0.2	−0.19	0.15
Fertilizer's price	−0.21	0.18	−0.2	0.17
Labour cost	−0.13	0.17	−0.15	0.08
Land	1.03	0.14	1.04	0.11
Capital	−0.02	0.16	−0.02	0.11

Based on this, as maize acreage increases and the capital spent on maize farming increases by 10 %, maize farming's profit will rise by 10.4 % and 2.0 %, respectively, based on the elasticity of profit for land and capital. For land [17,67], reported a similar value (0.99), but for capital, they reported a much lower value (0.01).

4.2. Analysis of profit efficiency

Based on the different models, Table 5 summarizes the PE estimates. According to our estimation method choice and model specification, pooled model PE scores are similar to those of TRE model, confirming the robustness underlying our estimates for inefficiency level. In the sampled farms, on average, 21.25 % of the maximum value of variable profit disappeared as a consequence of inefficiencies. PE varied widely across farms (0.03–0.96), supporting the hypothesis that less-efficient maize farmers can catch up to better-performing ones. Based on our findings, other empirical studies have found a similar mean PE. Maize farmers from Kenya's northern region were noted as having a mean PE equal to 0.68 by Ref. [70]. According to Ref. [71], the average profit inefficiency for maize farmers in the Eastern Cape Province was 0.69 [72]. estimated Eastern Ethiopia maize farmers' PE level to be 0.77, while [19] estimated Bangladeshi maize farmers' PE level to be 0.72.

4.3. Profit inefficiency determinants

In Table 3, the second part provides coefficient estimates for the inefficiency models described in equation (6) that are simultaneously estimated along with the SF models described in equation (5). In every case where we estimate an inefficiency model, the variable decreases the variance of the one-sided error or inefficiency term, increasing PE, and reducing PE. On the other hand, positive coefficients indicate that PE is being reduced. As expected, determinants of profit inefficiency have statistical significance in most cases. According to the results, the gender of farmers, household size, and number of household members have a negative effect on profit inefficiency in maize farms, while the distance of the farm, the amount of alkaline soil, the salinity of the soil, the presence of maize disease, and the likelihood of a natural disaster are positively related. All models estimated produce similar results.

4.4. Impacts of efficiency improvements on welfare

By estimating PE scores, frontier variable profits and variable profit losses resulting from inefficiency were calculated and then calculated how much farmers would increase their variable profits if profit inefficiency were eliminated. Table 6 presents the results. The predicted maximum variable profit levels for maize farmers are approximately US$477/ha, based on the same average PE scores of 0.81 and observed variable profit of US$326/ha. Approximately 46.31 % of profits are lost due to inefficiency, or US$151/ha. A significant amount of variable profit was lost by maize farmers because of inefficiency, according to this analysis. It is therefore necessary to implement policies that will help maize farmers improve their efficiency.

5. Discussion

5.1. Profit efficiency

A smallholder maize farmer's average profit efficiency score was 0.62, which means that production efficiency accounts for approximately 62% of maximum profit potential, whereas the remainder of the variation in realized profit and frontier profit stems from both technical and allocative inefficiencies, as previously revealed by a likelihood ratio test. It was also found that average profit efficiency among smallholders growing rice in northern Uganda stood at 59 % in Ref. [49]. In a study conducted by [53 in Northern Ghana, groundnut production using certified groundnut seeds (CGS) and conventional groundnuts (CG) were compared for profitability and profit efficiency. In terms of profit efficiency, CGS averaged 56.11 %, whereas CG averaged 53.54 %. Further analysis of smallholder maize farmers' profitability efficiency revealed a wide range of profitability efficiency, between 3 % and 96 %. Nonetheless, it is not surprising that profit efficiency levels differ so widely; similar results were achieved by Ref. [24] among smallholder maize farmers in Ghana, According to their findings, profit efficiency levels ranged from 2.4 % to 81.3 %, with a mean of 50 %.

5.2. Profit inefficiency determinants

According to the statistically significant negative estimates for gender, maize farming households headed by men are likely to have better performance than those headed by women. The majority of Kenyans who work on maize production are male, and they make all the decisions relating to it; therefore, they have a greater level of experience than women. Conversely, female-headed farming households have lower PE than male-headed farming households in Uganda, according to Ref. [49]. Larger farming households have a

Table 5
Models' profit efficiency summary.

Model	Mean	S.D.	Min	Max
Pooled	0.62	0.27	0.03	0.96
TRE	0.62	0.27	0.03	0.96

Table 6
Predicted frontier profits and losses.

Variable	Mean	Std. Dev.	Minimum	Maximum
Profit efficiency	0.62	0.27	0.03	0.96
Profit variable observed (US$/ha)	326	98.83	118.50	818.17
Variable profit maximum (US$/ha)	477	152.13	196.75	916.40
Profit loss	151	97	82.34	527.61
The difference	46.31			

higher PE since household size is negative and statistically significant. Based on these findings [73], also concur that larger households may have more labour resources and therefore be more motivated to work than hired workers. Profit inefficiency is negatively correlated with a farm's size, which implies that maize farms with a large area will be more efficient, as observed in Refs. [74,75].

The proximity between the residential area and the maize farm is significantly different according to Table 1. Profit inefficiency is significantly impacted by maize farm distance, according to the estimated inefficiency model. Farmer efficiency differs statistically more between those living far from their maize fields and those living near them, hence farmers living farther away are less efficient. Soils containing alkaline and soils containing salinity variables have significant parameter estimates, showing they contribute to increased inefficiency. Thus, improving soil quality could lead to a reduction in inefficiency. According to Refs. [73,74], farmers' efficiency was also improved by better soil quality. Natural disasters and diseases that affect maize also significantly reduced profit inefficiency. To reduce profit inefficiency, farmers can develop extension programs that detect, prevent, and mitigate maize diseases and natural disasters. Neither educational level nor prior maize-farming experience showed any statistically significant correlation with efficiency performance. A maize production trainings program and land ownership also had no significant impact on PE.

6. Conclusions and policy implications

For Kenyan maize farmers, TRE models were used to estimate PE and its influencing factors. In this study, robust and unbiased estimates are obtained by utilizing the SF model to take into account farm heterogeneity, and compare the estimates obtained from alternative functional forms. According to the results, PE estimates are insensitive to functional forms of the inefficiency term, but depend on its distribution. There is some evidence that farm heterogeneity does exist, but the PE estimates are not significantly affected by it. Input price estimates are both statistically significant and negative as expected. It is also found that profit and fixed inputs are positively correlated. In maize farming, variable profitability is elastic regarding output prices, but inelastic with regard to input prices. Profit is inelastic regarding land and capital.

Based on the PE analysis, Kenyan maize farming has a mean PE of 0.62, ranging from 0.03 to 0.96. Eliminating inefficiencies could result in an increase of 38 % in profits for maize farmers. It has been demonstrated that farmer characteristics and farm characteristics determine how much profit inefficiency varies among maize farmers. A farmer's household size, the farm's size, and the gender of the farmer all contribute to a negative effect on profit inefficiency, which is statistically significant. Profit inefficiency, however, is positively influenced by distance from home to maize farms, soil quality, maize disease, and natural disasters.

To mitigate the negative effects of natural disasters, maize farmers need adequate and accurate weather forecasts, as well as improved forecasting accuracy. To provide accurate market price information, forecasts should also be strengthened for input and output prices. To ensure maize farmers buy inputs and sell their outputs at a perfectly competitive price, contracts should be developed between producers, input suppliers, and output buyers.

Kenya's Uasin Gishu region faces increasing challenges due to climate change, including drought, saline intrusion, and maize disease. The infrastructure system must be adapted to climate change and mitigated to mitigate damage. It includes a road network, irrigating systems, anti-salinization systems, as well as ancillary facilities and equipment. It suggests that farm size and profit inefficiency have a significant negative relationship, suggesting that scale inefficiency and farmer efforts are partly to blame for profit inefficiency. To maximize profit levels, land-use policies should focus on improving farm size. Based on the analysis of profit elasticity, it is more efficient for the government to design price subsidy policies targeting maize prices than input prices if the goal is to improve farm profits.

In addition to this study's numerous contributions to the literature, there remain a number of issues that need to be explored further as part of further research on maize farming efficiency. There is an opportunity for future studies to apply more sophisticated econometric models that incorporate factors that contribute to transient and persistent inefficiency, such as those described in Ref. [76]–[86]. It is also possible to use newly introduced panel data models based on stochastic frontiers. These models can support decoupling and addressing inefficiencies in the allocation, transient, and persistent aspects of resource utilization as well as the underlying causes of all of these inefficiencies. As examples, systems-based approaches that utilize the production function and cost minimization first-order conditions have been proposed by Refs. [64,76,76,77].

Data availability statement

The data that has been used is confidential.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Vincent Ngeno: Writing - review & editing, Writing - original draft, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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