Heliyon 7 (2021) e05845

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Technical efficiency and technology gaps of sorghum plots in Uganda: A gendered stochastic metafrontier analysis

Philip Miriti [a,*], David Jakinda Otieno [a], Evans Chimoita [a], Edward Bikketi [b], Esther Njuguna [b], Chris O. Ojiewo [b]

[a] Department of Agricultural Economics, University of Nairobi, Kenya
[b] International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Nairobi, Kenya

ARTICLE INFO

Keywords:
Sorghum
Technical efficiency
Metafrontier
Plot manager

ABSTRACT

Sorghum plot managers in different locations have varying levels of resource endowment that in turn influence technical efficiency (TE). Therefore, plot managers operate at different levels of technology. The present study applied a stochastic metafrontier approach to assess TE and technology gaps of female, male and jointly-managed sorghum plots. A two limit-Tobit model was subsequently applied to assess determinants of TE. Results indicate that male-managed sorghum plots had the highest metafrontier technical efficiencies (MTEs) (61%, 56% and 15%) and technology gap ratios (TGRs) (98%, 92% and 20%) for Lira, Serere and Kumi districts, respectively compared to female and jointly managed plots. However, jointly managed plots had higher TE and TGRs compared to female plot managers but lower than those of the male-managed plots. Age, distance to plot and farmer group membership influenced TE positively while household size, years of farming sorghum and access to credit had negative effects on efficiency.

1. Introduction

Empirical analysis of farm technical efficiency (TE) gives useful insights on how farmers are utilizing the available inputs while technology gap ratios (TGRs) account for technology heterogeneity among producers (Battese and Rao, 2002). There is mixed literature about TE of plot managers. Most studies have documented that female plot managers have lower TE and TGRs compared to their male counterparts (see for example, Tesfaye et al., 2015; Sell et al., 2018; Danso-Abbeam et al., 2020). However, other studies such as Simonyan et al. (2015) show contrary results. The differences have often been linked to constraints that female farmers encounter in accessing and utilizing farm inputs (Gomez et al., 2020). For instance, Sell et al. (2018) attributed the low TE and TGRs for female plot managers to lack of official land titling that acts as a hindrance to accessing micro-credit since most mainstream banks require collateral for loans. Due to this, purchase of improved farm inputs and access to agricultural innovations becomes a challenge thus negatively affects women's efficiency (Sell et al., 2018). However, Doss (2018) noted that in situations where differences in access to inputs is controlled for, female farmers are as equally productive as their male counterparts.

Several past studies on gender gaps in TE and TGRs such as Marinda et al. (2006), Dadzie and Dasmani (2010) and Tesfaye et al. (2015) concentrated on female and male-owned plots. While other studies such as Sell et al. (2018) have assessed differences in TE among male, female and jointly managed plots in Uganda, empirical analysis of TGRs along gender lines on crops such as sorghum that receive little policy attention and are thus relegated to orphan-crops status, remain limited as most previous studies focused on staple cereals like maize.

In Uganda, sorghum is an important dryland cereal after maize and wheat in terms of production (Wang et al., 2015). It is majorly grown in the lowland areas of North and Eastern region and the South-Western highlands. The land under sorghum cultivation has increased from 280,000 ha to 370,000 ha in the last decade and it serves as a traditional delicacy mixed with legumes, as fermented or unfermented porridge and locally brewed beer. Industrially, it is used to produce sorghum syrup, starch, alcohol and edible oils (Adebo, 2020). The main sorghum varieties grown in Uganda include *NAROSOG-1*, *NAROSOG-2*, *NAROSOG-3*, *NAROSOG-4*, *SESO*-1, *SESO-2* and *SESO*-3 that are good for human food, forage, yeast and brewing (Lubadde et al., 2019). Production is done under pure and mixed stands and occupies approximately 400,000 ha of the total arable land (Tenywa et al., 2018).

* Corresponding author.
E-mail address: miritiphilip@gmail.com (P. Miriti).

https://doi.org/10.1016/j.heliyon.2020.e05845
Received 5 February 2020; Received in revised form 3 December 2020; Accepted 22 December 2020

The agricultural sector in Uganda accounts for 72% of all the employed women and nearly 76% of all rural women while around 65% of men in rural areas are employed in the sector (FAO, 2018). Despite the high percentage of women working in agriculture, only 20% own registered land (Sanjines et al., 2018). However, the over-emphasis of current agricultural policy and institutional support services in Africa on maize (Abdulai et al., 2018) and the neglect of sorghum provides an important justification to empirically assess TE and TGRs along gender perspective in order to inform food security and livelihood development initiatives for sustainability.

From a conceptual point of view, most previous studies have used household headship as the gender indicator in the efficiency model (Tesfaye et al., 2015; Addison et al., 2016; Gebremariam et al., 2019). This ignores the possibility that other household members besides the household head could be in charge of daily decisions on plot activities. Therefore, using the household head as the gender identifier constrains matching the individual in charge of the plot activities to input use and productivity (Peterman et al., 2011). In addition, while recent studies such as Osanya et al. (2020) offer insights on intra-household decision making on resource sharing, the extant literature on TE is predominantly based on farm-level data rather that plot-level data; this ignores the possibility of a farmer having multiple plots with varying characteristics (Owusu et al., 2017). The current study contributes to the literature on efficiency by using sex of the plot manager as the gender indicator on plot-level data.

2. Methodology

2.1. Sampling and data collection

The study used sex-disaggregated farm-level data that was categorized into female, male and jointly managed plots. This data was collected from a multistage sample of 362 farmers by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) in Uganda. First, three districts (Lira, Serere and Kumi district) were purposely chosen because they are major sorghum growing regions in Uganda. Lira district is located on the Northern region which contributes approximately 49% of the total production while Serere and Kumi districts are located on the Eastern region which contributes about 40% (Lubadde et al., 2019). Second, within the three districts, smaller administrative units with higher concentration of sorghum farms namely; Amach and Agali sub-counties in Lira, Katete in Kumi and Mukongoro in Serere were chosen. Finally, a probability proportionate to size method was used to distribute the sample across the three sites; 171 in Lira, 111 in Serere and 80 respondents in Kumi districts. A semi–structured questionnaire (ICRISAT, 2017) was applied in data collection using the Open Data Kit (ODK). Although this study did not involve use of human and/or animal samples/experiments, necessary ethical approval was obtained from the Institutional Ethics Committee (IEC) at ICRISAT. Further, informed consent was sought from all farmers before they were interviewed and assurance was given to them that any information collected would be treated with utmost confidentiality.

2.2. Analytical framework

Technology differences among farms can be accounted for using either a stochastic metafrontier approach or latent class model (Alvarez and Corral, 2010; Battese and Rao, 2002). In this study, we chose the metafrontier approach since it is applicable for analysis of either cross sectional data (which is available in this case) or panel data (Battese et al., 2004). As noted by Otieno (2011), the use of latent class modelling is limited to panel data.

First, the stochastic frontier for male, female and jointly managed sorghum plots assuming there are z regions were specified as:

$$Q^z_{ik} = f\left(X^z_{ijk};\beta^z_k\right)e^{\varepsilon k}\ i=1,2,3\ldots N;j\ ;k = Female\ managed\ plot(1),\ Male\ managed\ plot\ (2),\ Jointly\ mananged\ plot\ (3) \tag{1}$$

Q^z_{ik} represents sorghum output of z^{th} region from the i^{th} plot for the k^{th} plot manager group, X^z_{ijk} represents a vector for the j^{th} variable input used in z^{th} region by the k^{th} plot manager group in the i^{th} plot, β^z_k is a vector of coefficients associated with the independent variables for the stochastic frontier for the k^{th} plot manager group involved in z^{th} region, $e^{\varepsilon k} = v^z_{ik} - u^z_{ik}$ denotes a composite error term made of statistical noise v^z_{ik} and inefficiency term u^z_{ik} (Aigner et al., 1977).

Following Battese and Corra (1977), the variation of output from the frontier due to u^z_{ik} is defined by:

$$\gamma = \frac{\sigma^2_{u^z_{ik}}}{\sigma^2_{ik}}\ \text{and}\ 0\ \leq \gamma \geq 1 \tag{2}$$

where $\sigma^2 = \sigma^2_{uik} + \sigma^2_{vik}$

As noted by O'Donnell et al. (2008) the estimation of stochastic frontiers requires specification of the functional form since this can influence the efficiency estimate. Therefore, a likelihood ratio (LR) test was performed to test which functional form between Cobb-Douglas and trans-log fits the data well. The likelihood ratio test was specified as shown in Eq. (3) to test the null hypothesis that Cobb-Douglas provides a better fit for the data (Battese et al., 2004).

$$LR = -2\left\{ln\left(\frac{LH_0}{LH_1}\right)\right\} = -2\{Ln(LH_0) - Ln(LH_1)\} \tag{3}$$

where LH_0 = Log likelihood of Cobb Douglas functional form and LH_1 = Log likelihood of the alternate translog functional form.

LR = -2(-379.322–348.561) = 61.522.

The LR result does not support rejection of the hypothesis that Cobb-Douglas functional form would provide a better fit for the data, with a LR statistic of 61.522 compared to the chi-square critical value of 17.67 at 5% level and 10 degrees of freedom. The chi-square critical value was obtained from Kodde and Palm (1986) statistical table.

The Cobb-Douglas production frontier for male, female and jointly managed sorghum plots was therefore specified as shown in Eq. (4):

$$LnQ^z_{ik} = \beta^z_{0k} + \sum_{j=1}^{6}\beta^z_{ik}LnX^z_{ijk} + v^z_{ik} - u^z_{ik} : k = male\ managed\ plots\ (1),\ female\ managed\ plots\ (2), Jointly\ managed\ plot\ (3) \tag{4}$$

where Q^z_{ik} represents sorghum output (kg), X^z_{ijk} denotes vectors for variable inputs used in the plots such as sorghum seeds (kg), plot size (acres), family labour (person hours) and hired labour (person hours), β^z_{0k} represents the constant term, β^z_{ik} denotes coefficients of the inputs used, v^z_{ik} is statistical noise and u^z_{ik} is technical inefficiency.

The TE of the i^{th} plot in the z^{th} region with respect to the specific stochastic frontier is defined as the ratio of the observed output Q^z_{ik} to Q^{z*}_{ik} assuming that there are no inefficiencies in the production (Aigner et al., 1977; Battese et al., 2004):

$$TE^z_{ik} = \frac{Q^z_{ik}}{Q^{z*}_{ik}} = \frac{f\left(X^z_{ik}\ ;\ \beta^z_k\right)e^{u^z_{ik} - v^z_{ik}}}{f\left(X^z_{ik}\ ;\ \beta^z_k\right)e^{v^z_{ik}}} = e^{-u^z_{ik}} \tag{5}$$

Battese and Coelli (1988) noted that the most appropriate predictor of TE can be derived by re-writing Eq. (5) above as follows:

$$TE^z_{ik} = E\left[\exp\left(-u^z_{ik}\right)\right]\quad 0 \leq\ TE^z_{ik} \leq 1 \tag{6}$$

Subsequently, technology differences between the male, female and jointly-managed sorghum plots were addressed by estimating the metafrontier, which is assumed to be a smooth function that envelopes the specific male, female and jointly managed plots' stochastic frontiers (Battese and Rao, 2002). However, metafrontier estimation requires parameters obtained from initial stochastic frontier analysis. The metafrontier of the pooled sorghum plots' managers is given by:

$$lnQ_i^{z^*} = \beta_0^{z^*} + \sum_{j=1}^{6} \beta_j^{z^*} lnX_{ij}^{z^*} + \varepsilon_{ij}^{z}, \ j = 1, 2, 3, \ldots, j \tag{7}$$

where;

$Q_i^{z^*}$ represents the metafrontier output from z^{th} regions, $X_{ij}^{z^*}$ denotes vectors for variable inputs used in the plots such as seeds (kg), plot size (acres), family labour (person hours) and hired labour (person hours), $\beta_0^{z^*}$ represents the constant, $\beta_j^{z^*}$ denotes parameters to be estimated, * represents the metafrontier and ε_{ij}^{z} denotes the error term.

In this model, only the output and input variables were included. The metafrontier approach accounts for deviation between an observed level of output and the highest output that is realized in the group frontiers given a specific input level as well as accounting for the differences in technology (Battese et al., 2004).

The parameters $\beta_j^{z^*}$ of the metafrontier were estimated by solving a linear minimization problem, which was expressed as:

$$min \sum_{i=1}^{N} \left| \ln f\left(X_i^z, \beta^{z^*}\right) - lnf\left(X_i^z, \beta^z\right) \right|$$

$$s.t. \ \ln f\left(X_i^z, \beta^{z^*}\right) \geq \ lnf\left(X_i^z, \beta^z\right) \tag{8}$$

where $\ln f(X_i^z, \beta^{z^*})$ denotes the metafrontier and $lnf(X_i^z, \beta^z)$ are the plot manager frontiers (Battese et al., 2004).

With reference to the metafrontier, the observed sorghum output of the i^{th} plot with the k^{th} plot manager in the z^{th} region measured using the stochastic frontier shown earlier in Eq. (6) is given by Eq. (9):

$$Q_i^{z^*} = e^{-u_{ik}^z} \cdot \frac{f\left(x_{ijk}^z; \beta_k^z\right)}{f\left(x_{ijk}^z; \beta_k^{z^*}\right)} \cdot f\left(x_{ijk}^z; \beta_k^{z^*}\right) e^{v_{ik}^z} \tag{9}$$

In Eq. (9), $\frac{f(x_{ijk}^z; \beta_k^z)}{f(x_{ijk}^z; \beta_k^{z^*})}$ refers to the technology gap and it is a measure that lies between 0 and 1, hence:

$$TGR_{ik}^z = \frac{f\left(x_{ijk}^z; \beta_k^z\right)}{f\left(x_{ijk}^z; \beta_k^{z^*}\right)} \tag{10}$$

Therefore, $TE_{ik}^{z^*}$ can be derived through multiplying the TE from the stochastic frontier of the individual group by the TGR such that:

$$TE_{ik}^{z^*} = TE_{ik}^z \times TGR_{ik}^z \tag{11}$$

After estimation of MTEs, a two-limit-tobit model was applied to analyze determinants of TE because efficiency scores are bounded between 0 and 1 (Wang and Schmidt, 2002). While we recognize the observation by Schmidt (2011) that such a two-stage estimation procedure lacks consistency in assumptions regarding the distribution of inefficiencies, our approach is similar to the non-neutral stochastic frontier model proposed by Huang and Liu (1994). Specifically, Huang and Liu (1994) used a hybrid model comprising a stochastic frontier regression to obtain TE scores and a subsequent truncated regression to identify sources of efficiency. Moreover, in our case, the two-limt tobit approach is preferred over a single stage stochastic frontier model since it accounts for technology differences (Chen and Song, 2008; Otieno et al., 2014). The two-limit tobit model was expressed as follows.

$$u^* = X\beta + e$$

$$u = \left\{ \begin{array}{l} 0 \ if \ u^* < 0 \\ u^* \ if \ 0 < u^* \\ 1 \ if \ u^* > 1 \end{array} \right\} \tag{12}$$

where u^* denotes a continuous latent value of the TE score, u represents the observed value of the metafrontier TE score, X is a matrix of various socio-economic characteristics of sorghum farmers and other independent variables that may affect efficiency, βs represent vectors to be estimated and e is the random term.

The empirical data analysis involved use of the statistical package for social scientists (SPSS) to generate descriptive measures such as means and standard deviations for key variables; Frontier 4.1 software for TE analysis and; Shazam 11.1.4 software to estimate TGRs and bootstrapping technique to derive robust standard errors from the metafrontier parameters.

3. Results and discussions

3.1. Descriptive statistics

Majority of sorghum plot managers across the three study sites were adults with significant differences in average age. The plot managers had low formal education; less than 6 years of schooling on average (Table 1). This indicates that sorghum plot managers only attained primary level education.

The mean years of sorghum growing in the three study sites was over 7 years for all plot managers, with male plot managers having grown the crop for a longer period. The average sorghum plot size across all plot managers in the three study areas was significantly different, but less than 1 ha; hence they are assumed to be smallholder farmers. This is consistent with Cervantes-godoy (2015) who defined smallholder farmers as those owning less than 2 ha of land.

There are significant statistical differences among the three study areas in usage of farm inputs except fertilizer. Male plot managers had the highest average quantity of seed used and the mean person hours of family labour used across all the three districts. This corroborates the observation by Gebre et al. (2019) that male plot managers have greater access to farm inputs compared to female plot managers. There was no evidence of fertilizer use, except in Lira district where male plot managers recorded a minimal use of fertilizer perhaps due to contract farming with the brewery industry. This conforms with the observation by Tenywa et al. (2018) who found that fertilizer usage in sorghum growing especially in developing countries like Uganda is minimal. Even though Franke et al. (2018) observed that use of fertilizer increases the overall yield of cereals, Mbowa et al. (2015) showed that only less than 8% of farmers use the commonly available fertilizers in the market such as Diammonium Phosphate (DAP) and Calcium Ammonium Nitrate (CAN) (Mbowa et al., 2015).

The results showed significant statistical differences in institutional support services among the three study areas apart from access to credit. Generally, male plot managers across the study areas had the highest access to institutional support services variables compared to female plot managers. However, in a few cases, joint plot managers had a higher access compared to male plot managers. For example, in Kumi district, 63.16% of joint plot managers had access to extension services. Joint plot management was the most common type of sorghum plot management while the least was male plot management across the three districts.

3.2. Technical efficiency and technology gap ratios of female, male and jointly managed sorghum plots

Table 2 shows a comparative assessment of TE scores, TGRs and MTEs for Lira, Serere and Kumi districts. Male plot managers have the highest mean TE scores in Lira district. This is similar to the findings by Sell et al. (2018). However, female plot managers in Serere and Kumi districts have the highest mean TE with a low variation in standard deviation of

Table 1. Gender-disaggregated socio-economic characteristics of plot managers.

	Kumi			Lira			Serere			*p*- value for statistical differences between sites
	Male plot managers	Female plot managers	Joint plot managers	Male plot managers	Female plot managers	Joint plot managers	Male plot managers	Female plot managers	Joint plot managers	
Age	45.25	46.08	48.17	44.35	40.7	43.52	51.35	45.54	47.64	0.007***
Years completed in school	5	4.7	4.9	5.9	5.2	4.8	4.9	5.5	5.3	0.737
Average years of growing sorghum	17.37	15.09	18.68	7.48	8.92	9	20.41	17.57	15.32	0.000***
Pot size (mean Ha)	0.51	0.39	0.41	0.42	0.53	0.56	0.37	0.41	0.42	0.0002***
Average quantity of seed used (Kgs)	6.2	6.9	8.2	19.38	5.92	9.22	16.12	13.89	17.28	0.0001***
Average amount of fertilizer used (Kgs)	0	0	0	0.26	0	0	0	0	0	0.5708
Hired labour (average person hours)	6.63	3.85	9.26	0.9	0.9	7.07	15.64	6.86	5.74	0.0001***
Family labour (average person hours)	25.5	26.13	29.16	44.65	30.92	37.54	31.5	24.59	28.59	0.0203**
Access to credit (% yes)	29.41	12.5	31.58	20	16.13	34.12	35.14	17.65	38.6	0.3594
Farmer group membership (% yes)	40	23.58	23.68	52.73	48.39	45.88	24.32	23.53	36.84	0.0001***
Access to extension service (% yes)	50	44.12	63.16	40	32.26	41.18	45.95	29.41	43.16	0.0329**
Type of plot manager (%)	10	42.5	47.5	18.13	32.16	49.17	15.32	33.33	51.35	0.535

***, ** denote statistical significance at 1% and 5% levels, respectively.
Source: Survey Data (2017).

Table 2. Metafrontier results for female, male and jointly managed plots.

Model	Lira			Serere			Kumi		
	Female	Male	Jointly	Female	Male	Jointly	Female	Male	Jointly
TE *w.r.t* to plot management									
Mean	0.53934	0.61745	0.99799	0.60454	0.59424	0.73562	0.8985	0.71698	0.99858
Min	0.10856	0.26531	0.99798	0.26358	0.11973	0.46525	0.87591	0.36936	0.99858
Max	0.91904	0.82704	0.998	0.8482	0.95018	0.86889	0.91803	0.99981	0.99859
SD	0.23363	0.14063	0.000004	0.14604	0.26467	0.083442	0.013209	0.28081	0.000002
TE *w.r.t* to metafrontier (MTEs)									
Mean	0.45697	0.60525	0.59555	0.42112	0.55932	0.5198	0.086095	0.15021	0.10228
Min	0.00355	0.26531	0.29045	0.14574	0.07382	0.22417	0.050182	0.61194	0.46166
Max	0.869	0.82704	0.97636	0.74585	0.91304	0.84955	0.22315	0.28461	0.19182
SD	0.23604	0.15065	0.15778	0.1476	0.26968	0.1489	0.02836	0.7127	0.37256
TGRs									
Mean	0.83843	0.98218	0.59675	0.69844	0.92298	0.78798	0.095811	0.20812	0.10243
Min	0.20529	0.44761	0.29104	0.28656	0.53084	0.31165	0.056635	0.14792	0.046231
Max	1.00000	1.00000	0.97834	1.00000	1.00000	1.00000	0.24806	0.28466	0.19209
SD	0.21424	0.099213	0.02499	0.17319	0.14308	0.18458	0.03146	0.044289	0.037309

Source: Survey Data (2017).

0.000004 and 0.000002, respectively compared to male and jointly managed sorghum plots. The high mean TE in female-managed sorghum plots in these districts can be attributed to effective use of informal rotational labour groups locally referred to as 'Aleya' by female plot managers to overcome labour constraints as well as to share farming skills (Läderach et al., 2017). Jointly-managed sorghum plots have the highest mean TE across the three study sites.

The mean TE with respect to the metafrontier is lower across the three study sites for male, female and jointly managed sorghum plots compared to those with respect to the sorghum plot management frontiers. It is important to note that a higher TE does not necessarily translate to a high TGR because in real world there are other factors rather than technology that affect a farmers' ability to produce optimally. The fact that all mean TE with respect to the metafrontier are lower than 1 shows that there is potential to improve sorghum production by enhancing proper use of the available technologies. The mean TGR is highest for male sorghum plot managers across the three study sites compared to female and jointly-managed sorghum plots. Further, all categories of plot managers in Lira have the highest overall TGRs compared to those in Serere and Kumi districts. This is due to commercialization of sorghum farming in Lira district where farmers have contract farming arrangement with leading alcohol brewers such as Nile Breweries Ltd, Century and Uganda Breweries Ltd (Busuulwa, 2014). Therefore, they have relatively better access to farm inputs than farmers in other areas. Farmers in Kumi district, which lies in the Eastern part of Uganda where agriculture is less developed, have the lowest TGRs. The standard deviation of TGR is lowest among farmers in Kumi district, female (0.03), male (0.04) and jointly managed sorghum plots (0.04). Farmers in this district could be cultivating traditional sorghum varieties compared to other areas where both traditional and improved sorghum varieties are grown.

However, the maximum TGR is 1 for female, male and jointly managed plots in Serere district, as well as for female and male sorghum plot managers in Lira district. This implies that these farmers have exhausted the potential of existing technology (Battese et al., 2004) represented by sorghum variety in this case and therefore, further increases in sorghum production would require introduction of a better technology (sorghum varieties).

The distribution of TGRs is illustrated using kernel density plots. As shown in Figure 1, approximately 95% of male plot managers in Lira district had their TGRs between 0.85 to 1, 60% of the female plot

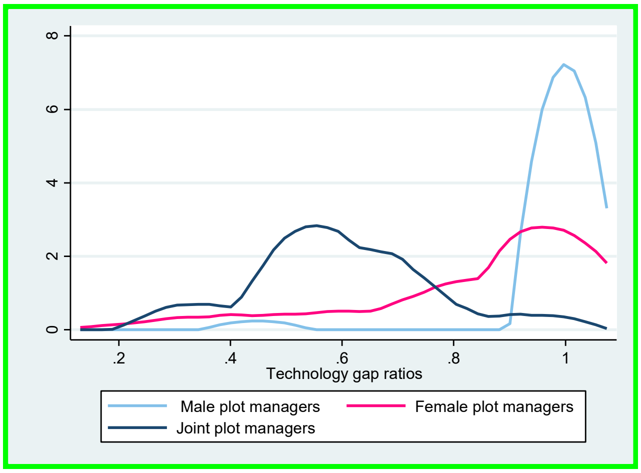

Figure 1. Distribution of TGRs in Lira district. Source: Survey Data (2017).

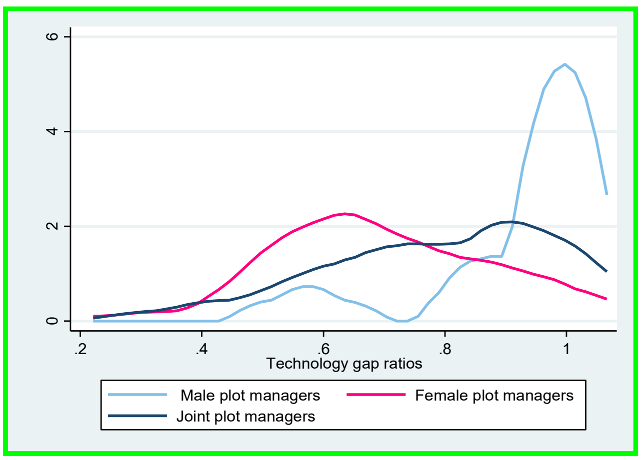

Figure 2. Distribution of TGRs in Serere district. Source: Survey Data (2017).

managers had their TGRs between 0.85 and 1, while the majority of joint plot managers (50%) had TGRs ranging from 0.45 to 0.65.

In Serere district, the TGRs of female plot managers and joint plot managers were concentrated between 0.45 and 0.65, while male plot managers had the highest TGRs ranging from 0.7 to 1 (Figure 2).

Majority of all sorghum plot managers in Kumi district had TGRs ranging from 0 to 0.25 as indicated in Figure 3. In common with Serere district, male plot managers in Kumi district had the highest TGRs compared to female and joint plot managers.

3.3. Determinants of technical efficiency

Considering that the metafrontier-tobit approach highlights determinants of efficiency while accounting for technology differences as opposed to one-step stochastic frontier model (Chen and Song, 2008; Otieno et al., 2014), we focus our discussion on the metafrontier results shown in Table 3. Nonetheless, we also provide the stochastic frontier results for completeness and comparison purposes.

All production inputs are significant except plot size. The insignificance of land size shows that sorghum output depends more on how well available land is used rather than amount of land. A similar finding on land use was reported by Otieno (2011) in the case of beef cattle production in Kenya. Sheng et al. (2019) also found that small plots are more manageable thus, increasing efficiency in using farm inputs as well as enabling close monitoring of farm activities compared to larger plots. Family labour has a positive and significant effect on sorghum efficiency. This is similar to the finding by Njuki and Bravo-Ureta (2019) on the

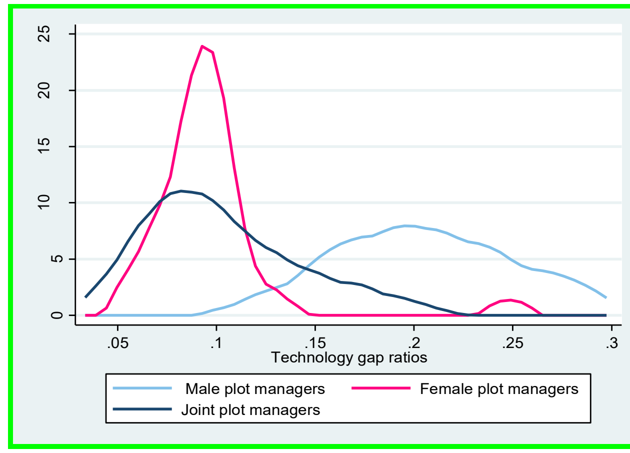

Figure 3. Distribution of TGRs in Kumi district. Source: Survey Data (2017).

positive effect of labour on irrigation productivity. Hired labour and amount of seed used influence sorghum efficiency positively. These two findings can be explained respectively, by the strict urge to recover costs of hired labour and the monotonicity condition of rational production where increments in input use should not decrease output (Coelli et al., 2005).

Age has a positive effect on TE. This is similar to Chiona et al. (2014) and Saiyut et al. (2017) who found that an increase in the age of a farmer tends to increase TE due to experience gained and networks that a farmer can exploit to produce more output. Household size has a negative effect on efficiency. An increase in the household size increases expenditure that the household incurs, therefore there might be little or no resources left to invest in farms thus reducing the farmer's efficiency level. This is similar to findings by Mango et al. (2015) in Zimbabwe where maize farmers who had larger households had lower TE. On the contrary, Mishra et al. (2015) found that household size increased TE of rice farmers in Bangladesh; perhaps due to availability of more free family labour.

Table 3. Metafrontier-Tobit results for determinants of technical efficiency.

Variables	Metafrontier-Tobit	
	Coefficient	Standard error
Production input parameters		
Constant	8.0059***	0.0132
Family labour	0.0200***	0.0071
Hired labour	0.0814****	0.0079
Seed	0.2485***	0.0325
Plot size	0.1200	0.1625
Efficiency effects		
Gender (1 = male)	0.0143	0.0101
Age	0.0007*	0.0004
Years completed in school	0.0028	0.0058
Household size	-0.0030*	0.0016
Years of farming sorghum	-0.0019***	0.0005
Distance to plot (meters)	0.000019***	0.000005
Access to credit (1 = yes)	-0.0227**	0.0112
Access to extension (1 = yes)	-0.0160	0.0098
Farmer group membership (1 = yes)	0.0545***	0.0105
Constant	0.1594***	0.0273
Log likelihood	354.0122	

***, **, *denote statistical significance at 1%,5% and 10% levels, respectively.
Source: Survey Data (2017).

The coefficient of years that a farmer has grown sorghum is negative and significant. This shows that as the years of growing sorghum increases, the TE of farmers tend to decline. This results to failure and reluctance of farmers to adopt modern innovations that are aimed at enhancing sorghum efficiency and they tend to stick to the old ways of sorghum farming. This is similar to the findings by Zalkuwi (2015) who noted that farmers who have grown sorghum for several years had lower productivity due to inefficiencies.

Distance of the sorghum plot from the homestead had a positive and significant effect on sorghum production efficiency. A longer distance indicates the possibility of farmers leasing in land for sorghum cultivation as well as having many scattered plots. Such farmers tend to be commercially oriented and they tend to use various farm inputs more efficiently thus leading to an increase in TE. This is consistent with the findings by Olarinde (2011) that maize farmers whose farm distance from the homestead was higher had a higher productivity, which was attributed to high TE of such farmers.

Access to credit had a negative and significant effect on the TE of sorghum plot managers. This could due to the use of credit for non-sorghum activities such as household consumption smoothening, education and health expenditures. This result is in line with Abate et al. (2019) who argued that red pepper farmers in Uganda used credit for household expenditure. Membership to farmer groups positively influenced TE. Farmer groups are useful avenues for peer learning and sharing of skills that possibly increase farmers' capacity to adopt new innovations such as crop varieties, thus improving their TE. Similarly, Abdulai et al. (2018) found that rice farmers in Ghana who belonged to farmer groups had high TE.

For completeness and comparison, results of the one-step stochastic frontier analysis are shown in Table 4 below.

The average TE for Serere, Lira and Kumi is 0.45 and approximately 50% of variation in sorghum output is due to technical inefficiency. The sum of coefficients for the input parameters is less than 1 meaning that sorghum producers in Uganda generally exhibit decreasing returns to scale. Also, plot size has a negative significant effect on TE; perhaps suggesting the difficulty of managing large land parcels as noted by Sheng et al. (2019). For brevity, we limit our discussion of these results since fewer variables are significant compared to those of the metafrontier-tobit analysis, besides the added advantage in the later model of capturing technology differences.

Table 4. One-step stochastic frontier model results with inefficiency estimates.

Variable	Coefficient	Standard error
Production input parameters		
Constant	4.891***	0.577
Family labour	0.363***	0.078
Hired labour	0.156***	0.031
Seed	0.238***	0.047
Plot size	-0.652***	0.112
Inefficiency		
Constant	1.874**	0.755
Gender (1 = male)	-0.035	0.096
Age	-0.345*	0.184
Years completed in school	-0.111*	0.063
Household size	0.187*	0.098
Years of farming sorghum	0.088	0.061
Distance to plot (meters)	-0.013	0.022
Access to credit (1 = yes)	0.022**	0.108
Access to extension (1 = yes)	0.153	0.107
Farmer group membership (1 = yes)	-0.052	0.106
Sigma-squared	0.503***	0.089
Gamma	0.504**	0.231
Maximum TE	0.789	
Minimum TE	0.118	
Mean TE	0.446	
Log likelihood function	-370.952	

***, **, * Statistical significance levels at 1%, 5% and 10%, respectively.

This study has made useful contributions to the literature in two fronts; analysis of TE and TGRs for a critical crop in developing countries' household food security – sorghum, that was hitherto neglected in empirical research and development policy and; a gendered analysis using plot-level rather than farm-level data. We acknowledge as a limitation, the potential reduction of the consistency of estimates arising from two-step analysis procedure. Therefore, our results should be interpreted with some caution. Use of one-step equations when technology differences are not the focus of analysis and large sample sizes suggested by Kaplan et al. (2014) and Springate (2012) would improve the reliability of model results.

4. Conclusion and recommendations

The study applied a stochastic metafrontier approach to assess TE, TGRs and determinants of TE in sorghum plots in Uganda. Male managed sorghum plots across the three study areas had a higher MTE and TGR compared to female and jointly managed sorghum plots. However, the MTE and TGR of jointly managed plots were higher than female managed plots but lower compared to male managed plots. Results show that majority of the sorghum plot managers use the available technology sub-optimally, hence their output is lower than the potential levels. The age of plot managers and years completed in school influence TE positively, while the household size affects efficiency negatively.

There is need to provide technical support aimed at sorghum plot managers in order to facilitate appropriate use of the available technology by managers who are producing sub-optimally so as to increase sorghum yields. This includes interventions such as educating farmers on how to grow sorghum using modern techniques that incorporate climate smart agriculture, how to handle resistant pests and diseases. In addition, introduction of high yielding sorghum varieties that are favorable to each specific district enable sorghum plot managers who have exhausted the potential of available varieties by attaining maximum TGRs of 1, to achieve further productivity gains. In order to empower female sorghum plot managers and bridge the TE and TGRs gaps between them and the male-managed sorghum plots, development interventions that seek to build technical capacity of female sorghum plot managers are recommended.

Results highlight critical roles that farmer groups play in influencing TE. Policy interventions aimed at creating a conducive environment for farmer groups to operate such as legal registration and providing farmer group leaders with managerial and record keeping skills. Better targeting of credit by financial institutions through consideration of various types of farmers (subsistence, transitioning, contract, specialized and diversified commercial farmers) and continuous monitoring of credit recipients to ensure that the credit given is used appropriately for targeted farm-related activities are also suggested. Future research that make comparison of efficiencies of different cereal crops and/or livestock enterprises would provide useful insights on disparities among farmers in similar environments and technology space.

Declarations

Author contribution statement

Philip Miriti: Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

David Jakinda Otieno, Evans Chimoita: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

Edward Bikketi, Esther Njuguna: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data.

Chris O. Ojiewo: Conceived and designed the experiments.

Funding statement

This work was supported by International Crops Research Institute for the Semi-Arid Tropics (ICRISAT).

Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

Supplementary content related to this article has been published online at https://doi.org/10.1016/j.heliyon.2020.e05845.

References

Abate, T., Dessie, A., Mekie, T., 2019. Technical efficiency of smallholder farmers in red pepper production in North Gondar zone Amhara regional state, Ethiopia. J. Econ. Struct. 8 (1), 18–32.

Abdulai, S., Zakariah, A., Donkoh, S., 2018. Adoption of rice cultivation technologies and its effect on technical efficiency in Sagnarigu District of Ghana. Cogent Food Agricul. 4 (1), 1–6.

Addison, M., Ohene-Yankyera, K., Fredua-Antoh, E., 2016. Gender role , input use and technical efficiency among rice farmers at Ahafo Ano North District in Ashanti Region of Ghana. J. Food Secur. 4 (2), 27–35.

Adebo, A., 2020. African sorghum-based fermented foods: past, current and future prospects. Nutrients 12 (4), 1111–1116.

Aigner, D., Lovell, C., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. J. Econom. 6 (1), 21–37.

Alvarez, A., Corral, J., 2010. Identifying different technologies using a latent class model: extensive vs intensive dairy farms. Eur. Rev. Agric. Econ. 37 (2), 231–250.

Battese, G., Corra, G., 1977. Estimation of a production function model: with application to the pastoral zone of Eastern Australia. Aust. J. Agric. Econ. 21 (3), 169–179.

Battese, G., Coelli, T., 1988. Prediction of firm-level technical efficiencies with a generalised frontier production function and panel data. J. Econom. 38 (1), 387–399.

Battese, G., Rao, D., O'odonnell, C., 2004. A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. J. Prod. Anal. 91–103 (2002).

Battese, G., Rao, D., 2002. Technology gap, efficiency, and a stochastic metafrontier function. Int. J. Bus. Econ. 1 (2), 87–93.

Busuulwa, B., 2014. Contract Farming Boom from Ugandan Beverage Makers - the East African. https://www.theeastafrican.co.ke/business/Contract-farming-boom-Uganda-beverage-makers/2560-2451530-5dcdtvz/index.html. (Accessed 22 July 2019).

Cervantes-godoy, D., 2015. Strategies for Addressing Smallholder Agriculture and Facilitating Structural Transformation. OECD Food, Agriculture and Fisheries Papers, No. 90. OECD Publishing (90).

Chen, Z., Song, S., 2008. Efficiency and technology gap in China's agriculture: a regional metafrontier analysis. China Econ. Rev. 19 (2), 287–296.

Chiona, S., Kalinda, T., Tembo, G., 2014. Stochastic frontier analysis of the technical efficiency of smallholder maize farmers in Central Province, Zambia. J. Agric. Sci. 6 (10), 108–118.

Coelli, T., Rao, D., Battese, G., 2005. An Introduction to Efficiency and Productivity Analysis, second ed. Kluwer Academic Publishers, Boston.

Dadzie, S., Dasmani, I., 2010. Gender difference and farm level efficiency: metafrontier production function approach. J. Dev. Agric. Econ. 2 (February), 441–451.

Danso-Abbeam, G., Baiyegunhi, L., Ojo, T., 2020. Gender differentials in technical efficiency of Ghanaian cocoa farms. Heliyon 6 (5), 4–12.

Doss, C.R., 2018. Women and agricultural productivity: Reframing the Issues. Dev. Policy Rev. 36 (1), 35–50.

FAO, 2018. Country Gender Assessment Series: National Gender Profile of Agriculture and Rural Livelihoods Uganda. Food and Agriculture Organization of the United Nations, Kampala, Uganda.

Franke, A., Vanlauwe, B., Giller, K., 2018. Sustainable intensification through rotations with grain legumes in Sub-Saharan Africa: a review. Agric. Ecosyst. Environ. 261 (September), 172–185.

Gebre, G., Isoda, H., Rahut, D., Amekawa, Y., Nomura, H., 2019. Gender differences in agricultural productivity: evidence from maize farm households in southern Ethiopia. Geo J., 0123456789

Gebremariam, H., Weldegiorgis, L., Tekle, A., 2019. Efficiency of male and female as irrigated onion growers. Int. J. Veg. Sci. 3 (January), 7–13.

Gomez, S., Laura, R., Louhichi, K., 2020. The Role of Smallholder Farms in Food and Nutrition Security. Springer, Cham, Switzerland.

Huang, C., Liu, T., 1994. Estimation of a non-neutral stochastic frontier production function. J. Prod. Anal. 5, 171–180.

ICRISAT, 2017. Household Survey Questionnaire. International Crops Research Institute for the Semi-Arid Tropics, Nairobi, Kenya.

Kaplan, R., Chambers, D., Glasgow, R., 2014. Big data and large sample size: a cautionary note on the potential for bias. Clin. Trans. Sci. 7 (4), 342–346.

Kodde, D., Palm, F., 1986. Wald criteria for jointly testing equality and inequality restrictions. Econ. Soc. 54 (5), 1243–1248.

Läderach, P., Mwongera, C., Lamanna, C., Acosta, M., Ampaire, E., 2017. Know what drives the adoption of climate-smart agriculture across different scales. Cgsspace 2 (10), 12–17.

Lubadde, G., Ebiyau, J., Andiku, J., Wandulu, M., 2019. Sorghum Production Handbook for Uganda. National Semi Arid Resources Research Institute of the National Agricultural Research Organisation (NaSARRI-NARO), *Uganda.* Uganda.

Mango, N., Makate, C., Hanyani-mlambo, B., Siziba, S., Lundy, M., 2015. A stochastic frontier analysis of technical efficiency in smallholder maize production in Zimbabwe: the post-fast-track land reform outlook. Cogent Econ. Finance 6 (1), 1–14.

Marinda, P., Bangura, A., Heidhues, F., 2006. Technical efficiency analysis in male and female-managed farms: a study of maize production in west Pokot district, Kenya. International Association of Agricultural Economists Conference.

Mbowa, S., Luswata, K., Bulegeya, K., 2015. Are Ugandan Farmers Using the Right Quality Inorganic Fertilizers? (No. 56). Economic Policy Research Centre Kampala, Uganda.

Mishra, A., Mottaleb, K., Khanal, A., Mohanty, S., 2015. Abiotic stress and its impact on production efficiency: the case of rice farming in Bangladesh. Agric. Ecosyst. Environ. 199, 146–153.

Njuki, E., Bravo-Ureta, B., 2019. Examining irrigation productivity in U.S. agriculture using a single-factor approach. J. Prod. Anal. 51 (2–3), 125–136.

O'Donnell, Christopher J., Prasada Rao, D.S., Battese, George, 2008. Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. Empir. Econ. 34 (2), 231–255.

Olarinde, L.O., 2011. Analysis of technical Efficiency differentials among maize farmers in Nigeria. The African Economic Research Consortium, Nairobi,Kenya.

Osanya, J., Adam, R., Otieno, D., Nyikal, R., Moti, J., 2020. An analysis of the respective contributions of husband and wife in farming households in Kenya to decisions regarding the use of income: a multinomial logit approach. Wom. Stud. Int. Forum 83, 10–19.

Otieno, D., 2011. Economic Analysis of Beef Cattle Farmers ' Technical Efficiency and Willingness to Comply with Disease Free Zones in Kenya. Doctoral Thesis. Newcastle University, United Kingdom.

Otieno, D., Hubbard, L., Ruto, E., 2014. Assessment of technical efficiency and its determinants in beef cattle production in Kenya. J. Dev. Agric. Econ. 6 (6), 267–278.

Owusu, V., Donkor, E., Owusu-Sekyere, E., 2017. Accounting for the gender technology gap amongst smallholder rice farmers in Northern Ghana. J. Agric. Econ. 2011 (456), 45–57.

Peterman, A., Quisumbing, A., Behrman, J., Nkonya, E., 2011. Understanding the complexities surrounding gender differences in agricultural productivity in Nigeria and Uganda. J. Dev. Stud. 47 (10), 1482–1509.

Saiyut, P., Bunyasiri, I., Sirisupluxana, P., 2017. The impact of age structure on technical efficiency in Thai agriculture. Kasetsart J. Social Sci. 40 (539–545).

Sanjines, M., Oput, R., Burke, C., 2018. Land administration domain model and its contribution to monitoring of land governance in Uganda. In: 2018 World Bank Conference on Land and Poverty, 53. World Bank, Washington DC, pp. 1689–1699.

Schmidt, P., 2011. One-step and two-step estimation in SFA models. J. Prod. Anal. 36 (2), 201–203.

Sell, M., Bäckman, S., Tettehanang, B., Niemi, J., 2018. The unequal efficiency gap: key factors influencing women farmer ' s efficiency in Uganda. Cogent Food Agricul. 4 (1), 1–18.

Sheng, Y., Ding, J., Huang, J., 2019. The relationship between farm size and productivity in agriculture: evidence from maize production in Northern China. Am. J. Agric. Econ. 101 (3), 790–806.

Simonyan, J., Umoren, B., Okoye, B., 2015. Gender differentials in technical efficiency among maize farmers in Essien Udim local government area, Nigeria. Int. J. Econ. Manag. Sci. 1 (2), 17–23.

Springate, S., 2012. The effect of sample size and bias on the reliability of estimates of error: a comparative study of Dahlberg's formula. EJO (Eur. J. Orthod.) 34 (2), 158–163.

Tenywa, M., Kalibwani, R., Nyamwaro, S., Mogabo, J., Moses, M., Buruchara, R., Oluwole, F., 2018. Innovation opportunities in sorghum production in Uganda. FARA Res. Rep. 2 (18), 20.

Tesfaye, S., Yami, M., Begna, B., 2015. Gender differentials in scale and technical efficiencies among improved wheat variety growers in wheat belt areas of Ethiopia: a data envelopment analysis (DEA). J. Econ. Sustain. Dev. 6 (1), 2222, 1700. Retrieved from. www.iiste.org.

Wang, H., Schmidt, P., 2002. One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. J. Prod. Anal. 103 (3), 239–248.

Wang, S., Heisey, P., Schimmelpfennig, D., Ball, E., 2015. Agricultural Productivity Growth in the United States: Measurement , Trends and Drivers. U.S. Department of Agriculture, Economic Research Service, Washington. July 2015.

Zalkuwi, J., 2015. Socio – economic factors that affect sorghum production in Adamawa State , Nigeria. Int. J. Sci. Res. 4 (2), 1610–1614.