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EVALUATION OF FARM TECHNICAL EFFICIENCY AMONG SMALLHOLDER COTTON FARMERS IN ZIMBABWE

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ABSTRACT

There are few efficiency studies that have been done in Zimbabwe. The current study bridges the literature gap by carrying a frontier efficiency analysis using survey data obtained from the cotton producing farms in three selected provinces. Results from a restricted stochastic frontier model, with a three-stage procedure, indicated existence of technical inefficiency in cotton production. Our findings proved that the results from the traditional frontier models are biased. The model displays that farmers' educational background, farm size, soil type, the application of fertilizer (both basal and top dressing), access to inputs, reliability of rainfall, farmers' involvement in off-farm work and cotton production experiences significantly ($p=0.05$) contribute to input use efficiency. A quantile regression showed that knowledge indicators were pivotal in increasing farmers' efficiency in cotton production. The impact of cotton production experience on technical efficiency was positive, though not significant, in the middle and higher efficiency percentiles. Notably, having a basic education (completing primary education only) was not sufficient in obtaining higher efficiency. Results indicated that the provision of agricultural training and the development of sound cotton extension services will assist farmers to acquire new technologies and decision-making capabilities about farm productivity that will ultimately raise the resource use efficiency in cotton production.

Keywords: Decision-making; Farm productivity; Knowledge; Modelling; Production factors

INTRODUCTION

Cotton ranks second from tobacco among the cash crops in Zimbabwe and is considered a strategic crop because it contributes to a major proportion of rural employment and foreign exchange (Poulton and Mlambo. 2008). Therefore, the crop is an important commodity in the

agricultural sector and the economy of Zimbabwe. Unfortunately, in Zimbabwe the cotton production is low compared to other countries. In Zimbabwe, the cotton is mainly grown by small-scale farmers in marginal and arid areas, on small (< 2 ha) land holdings and production levels are constantly fluctuating on the lower (28 000 MT/yr) side (Figure 1). The global yield is forecast at 0.765 tons per hectare while the Zimbabwean yield is 0.5 tons per hectare, in the past 5-years. However, in recent years, cotton production has been very unstable ranging between 351,000MT in 2011/2012 and 28,000MT in 2015/16 seasons (Cotton Indaba Taskforce. 2012). This has been so despite an established national ginning capacity of over 600,000MT (FAO, 2019). Yield of cotton is dependent on the environment in which it is grown and management practices of the cropping system (Poulton and Mlambo. 2008). Jari (2009) noted that many factors influencing cotton production viz. quality seed, fertilizers and reliable rainfall has significantly affected obtaining higher cotton yield. Some researchers explored factors such as education, fertilizer, land preparation, plant protection measures, irrigation and seed as main factors affecting cotton production (Machethe et al., 2008). These researches agreed that cotton is an input intensive crop so limited inputs can greatly reduce the production quantity and quality.

Cotton production in Zimbabwe is mainly controlled by the state so, everything related to cotton has a national significance and priority. Attaining higher (>500 kg/ha) yields is an objective for those involved in the entire cotton value chain. In efforts to increase production, a presidential input scheme was launched and farmers are given the inputs for free through the COTTCO. Unfortunately, the yield levels are still low (Figure 1) suggesting that there could be other factors behind this low productivity. This clearly points to farm technical inefficiencies as the main factor responsible for the low cotton yield in Zimbabwe. The smallholder farmers are obtaining an average cotton yield of <500 kg/ha which is far below the yield in the early 1980s (Cotton Indaba Taskforce, 2012; FAO, 2019). Technical efficiency (TE) is defined as the ability of a farm to attain the highest level of output given a set of inputs (Mathijs and Vranken, 2001). The determination of the farm's TE enhances the farmer's decision-making process by assessing whether he/she is using the inputs correctly (Reimers and Klasen, 2013). Briefly, the estimation of TE enables a farmer to know if they are properly using the inputs at his/her disposal, as well as the possible income gains resulting from an improvement of the inputs' use.

Previous studies that looked at the relationship between total land under the cotton and yield showed no specific relationships between total hectareage and the yield (Reimers and Klasen, 2013). In other studies, it is agreed that adoption and dissemination of innovative farming practices can improve productivity and income (Awotide et al. 2013; Karimov, 2014). Hence, effective resource use and a well-organized farm management are essential for sustainability and high farm productivity. In this regard, education becomes an essential factor in improving the efficiency of

resource utilization at a farm (Battese and Coelli, 1995; Manevska-Tasevska, 2013). Karimov (2014) states that education is a strong complement for many factors of production utilized in technical crop production. Education was also found to have a positive impact on agricultural productivity worldwide (Reimers and Klasen, 2013) hence the access to modernised agricultural knowledge has become a priority to the cotton farmers because most of them are not knowledgeable in farm production (Mathijs and Vranken, 2001). There are new market mechanisms that are evolving especially for cash crops where there is a need to have new sets of skills to run farming efficiently. Educating farmers to be efficient and productive under a changing environment has become the primary concern for all cotton stakeholders.

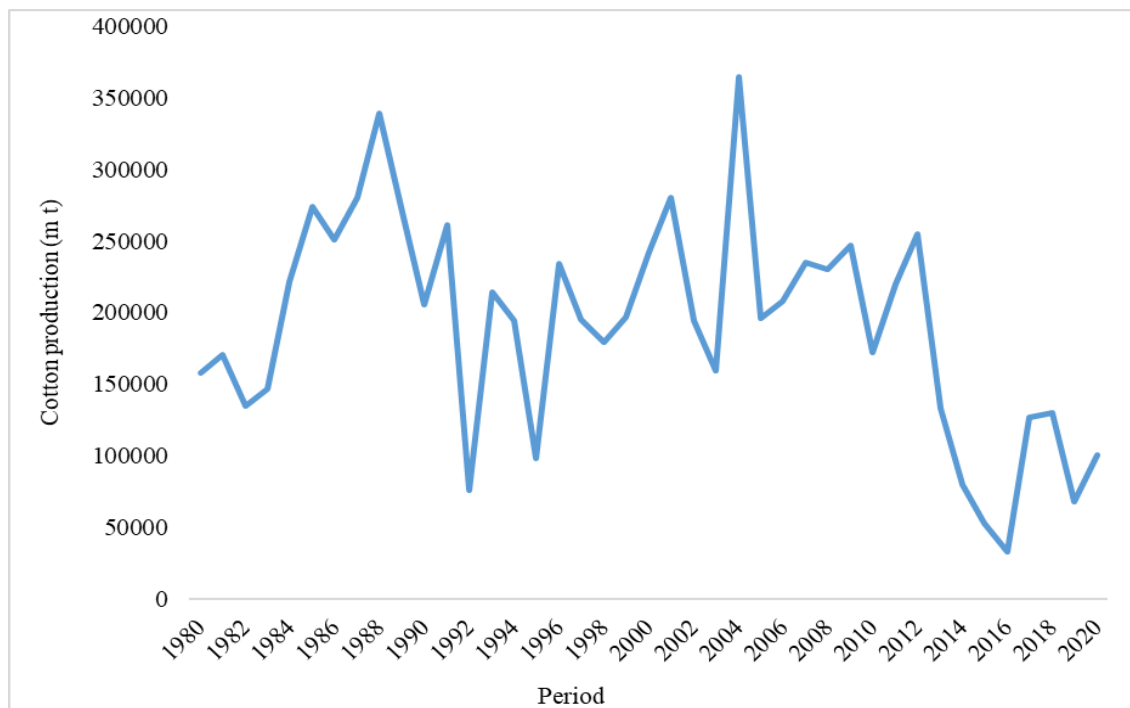


Figure 1: Cotton Production Trends in Zimbabwe from 1980 to 2020 (COTTCO, 2020)

The cotton production levels in Zimbabwe have been fluctuating from low to high since 1980 to date. The production was high (average 281137.6 MT) from 1983 to 1991. However, there was a notable sharp decrease from 2013 to 2020 (Figure 1).

Regardless that the government is providing free inputs for cotton production, farmers shoulder the burden of the crop, to meet annual production targets (Cotton Indaba Taskforce, 2012). When the farmers receive the input through COTTCO (state's semi-controlled organization) they are obliged to market 100% of the harvest to the COTTCO at predetermined prices. However, since the price of the seed cotton is controlled there is small price change depending on the quality so farmers can

achieve higher margins only by increasing yields and efficiently using input resources (Mathijs and Vranken, 2001; Tashrifov, 2005). Clearly yield figures at the national level show that the cotton production has decreased since 1980 (Cotton Indaba Taskforce, 2012). Suggesting that the decline could be due to the inefficient use of resources at the farm but the official statistics on cotton production do not factor in resource use data, it is therefore challenging to obtain reliable data on the intensity of resource utilization in cotton production. Nevertheless, some studies done elsewhere outside Zimbabwe have reported on the over- or under-utilization of inputs in agriculture (Cotton Indaba Taskforce, 2012; Tschirley et al., 2010). Generally, in Zimbabwe, the cotton production levels are low when compared to other countries with analogous climate conditions and the cost of producing cotton is relatively high. In response to this, the strengthening of the efficiency of cotton production is a major concern in the Zimbabwean cotton sector. This study looked at this issue in the context of frontier efficiency analysis by considering some of the factors that are assumed to influence cotton production.

The efficient use of inputs in cotton production is thus an open question because smallholder cotton farmers need to adapt the use of their inputs, such as fertilizers, due to the high costs incurred in their purchase. The overall purpose of this study was to analyse the technical efficiency of smallholder cotton farms in Zimbabwe. Essentially, the paper aimed at detecting the technical efficiency of the farms in smallholder cotton farms. The specific objectives were: 1) to assess the technical efficiency (TE) of cotton producers through theoretically consistent stochastic frontier model (SFM); 2) to evaluate significance of some farm related factors which influence the households' input use in cotton production, and 3) to evaluate the effect of knowledge indicators on resource use efficiency at farm level.

MATERIALS AND METHODOLOGY

Study site

The study was carried out in three major cotton producing provinces of Zimbabwe. The selected three provinces are Midlands, Masvingo, and Mashonaland Central. Midlands is 274 km south-west of Harare, Masvingo is 293 km in the southern direction, and Mashonaland Central is 88 km North West from the capital (Figure 2). Agriculture particularly the cotton production is major economic activity in these provinces.



Figure 2: The selected provinces shown by the black (Source: www.mapsofworld.com)

Data collection and sampling procedure

Primary data was collected by well-structured farm surveys in three major cotton producing provinces of Zimbabwe. The surveys were done between November 2021 to March 2022. The surveys used quantitative questionnaires to interview randomly selected cotton farmers selected according to the major sources (government aided, self-funded or contract from other organisations) of production inputs in the selected provinces (Figure 3). In the interviews, farmers were asked to recall input-output data related to the cotton-growing season of 2020-

2021. The questionnaire was pre-tested by interviewing 50 randomly selected farmers in the Muzarabani district, Mashonaland Central province. Pre-testing was important in highlighting potential problems that could arise during the interview to both the enumerators and the respondents. COTTCO extension workers who had good knowledge of the study areas and cotton production practices of the farms were selected for enumeration. Then, they were trained for one week to clarify the structure and the administration of the questionnaire. The study used a multistage sampling where three major cotton producing provinces were purposely selected in Zimbabwe. Then three districts were randomly selected from each of the three provinces. Generally, a district had 40 wards so 8 wards were randomly selected from each district hence each province had 24 selected wards in total. From each ward, 15 cotton farmers were randomly selected from a farmer list obtained from a COTTCO extension worker in the selected ward. This means a total of 360 farmers were sampled per province and 1080 farmers for the whole study (Figure 2).

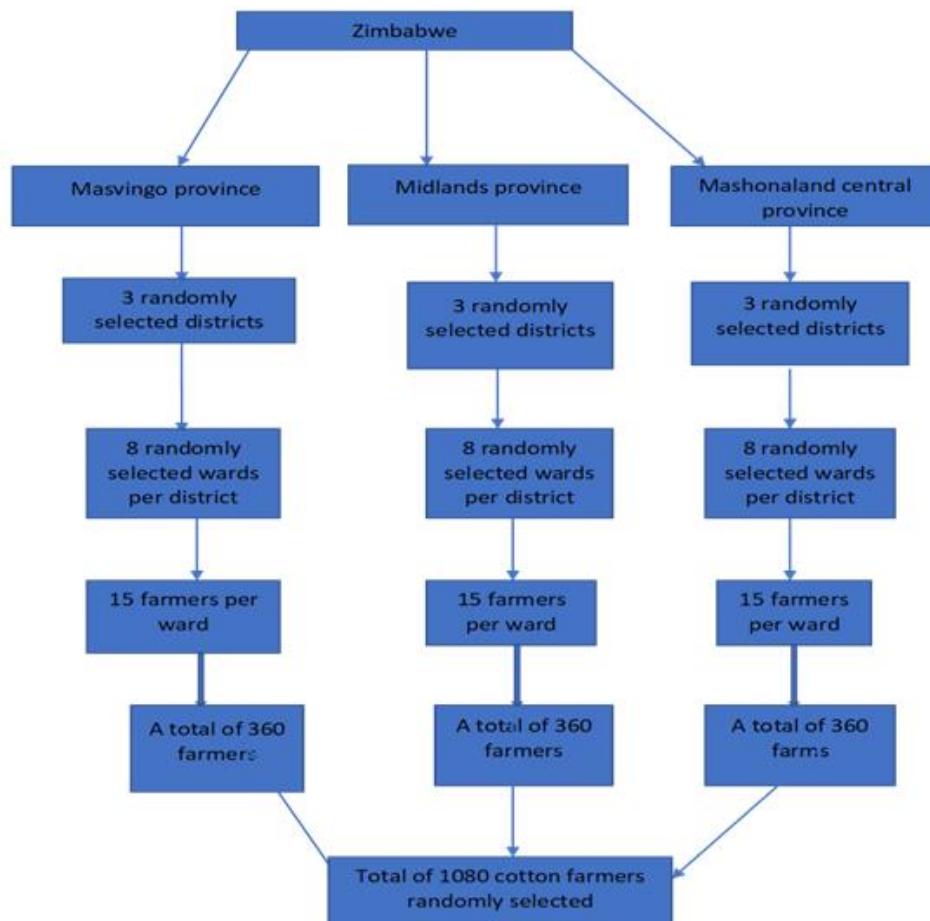


Figure 3: The multi-stage sampling procedure used in data collection

DATA ANALYSIS

Stochastic frontier modelling

A stochastic frontier approach as described by Aigner et al. (1977) was used:

$$y_k = f(x_{k,i}; \beta_i) \exp(v_k - u_k), \quad (\text{Eqn. 1})$$

Where: y_k was the production quantity of the k^{th} sample farm, $f(.)$ describes a chosen functional form and $x_{k,i}$ and β_i were vector of inputs and their associated parameters respectively.

The model was stochastic, because the traditional error term equals $v_k - u_k$. u_k was a random error and independently and identically distributed $\{N(0, \delta^2)\}$. This included all errors that occurred due to the model misspecification and other factors like random shocks that were beyond the cotton farmers' control. u_k is the asymmetric and non-negative error term which captured failures in resources utilization. The resultant inefficiency indicator was independent, not only from v_k , but also from y_k and $x_{k,i}$ used in the stochastic frontier model. This assumption was necessary to avoid an endogeneity problem. With the input vector x_k , the k^{th} farm's technical efficiency (i.e more efficient use of inputs) was equal to the ratio of the k^{th} farm's observed production related to the production defined by the frontier:

$$TE_k = \frac{F(x; \beta) e^{(v_k - u_k)}}{F(x; \beta) e^{(-u_k)}} = \exp(-u_k), \quad (\text{Eqn. 2})$$

Where TE_k is the technical efficiency of the k^{th} farm, $F(.)$ describes a chosen functional form and x and β were vector of inputs and their associated parameters respectively.

The technical efficiency (TE) score is between 0 and 1. A farm is fully efficient when it equals 1 and fully inefficient when is 0.

The research aimed at establishing a theoretically consistent stochastic frontier model where essential microeconomic assumptions should be met, including the monotonicity and curvature properties. Henningsen and Henning (2009) proposed a 3-stage approach and showed how the monotonicity restriction can be successfully applied in the frontier context. The first stage involves a simultaneous estimation of Eqn. (1) and (2) as described by Karimov (2014). This study used a translog functional form, which had independent variables that were at least equal to $\frac{1}{2}(n+2)(n+1)$ and fulfilled the second-order flexibility condition:

$$\ln y_k = \beta_0 + \sum_{i=1}^n \beta_i \ln x_{k,i} + \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \beta_{i,j} \ln x_{k,i} \ln x_{k,j} + v_k - u_k \quad (\text{Eqn.3})$$

as well as the theorem by Battese and Coelli (1995) that entails the symmetry of all Hessians ($\beta_{ij} = \beta_{ji}$).

$u_k = \delta_0 + \sum_m \delta_m Z_{k,m} + \varphi_k$ (Eqn. 4) where: u_k denotes the mean technical inefficiency obtained from Eqn. (3). $Z_{k,m}$ describes the explanatory attributes and φ_k is the non-negative random error represented by the truncation of the normal distribution with a 0 mean and variance, σ_μ^2 . δ_0 and δ_μ are the inefficiency parameters to be estimated. The monotonicity restriction is imposed in stage two. The second stage involves the solving of a quadratic optimization model by imposing monotonicity on parameters via asymptotically equivalent minimum distance estimator, together with the parameters of the production frontier, $\frac{\hat{\alpha}}{\beta}$, and their covariance matrix, $\frac{\hat{\alpha}}{\Omega_\beta}$ which were extracted from stage 1.

$\frac{\hat{\alpha}}{\beta^0} = \arg \min \{(\frac{\hat{\alpha}}{\beta^0} - \frac{\hat{\alpha}}{\beta})\Omega_\beta^{-1}(\frac{\hat{\alpha}}{\beta^0} - \frac{\hat{\alpha}}{\beta}): f_i(x; \frac{\hat{\alpha}}{\beta^0}) \geq 0 \forall_i, x\}$, (Eqn. 5) where; $\frac{\hat{\alpha}}{\beta^0}$ describes the model's restricted parameters, $f_i(x; \frac{\hat{\alpha}}{\beta^0}) \geq 0 \forall_i, x$ is the monotonicity restriction imposed on the model. The last stage the integrates these parameters to Eqn. (4) and simultaneously estimates it with Eqn. (5):

$$\ln y_k = \omega_0 + \omega_1 \ln Y + v_k^0 - u_k^0 \quad (\text{Eqn. 6})$$

$$u_k = \sigma_0^0 + \sum_m \sigma_m^0 m Z_{km} + \eta_k^0 \quad (\text{Eqn. 7})$$

Where $Y = f(x, \frac{\hat{\alpha}}{\beta^0})$; which was obtained from eqn. (5), ω_0 and ω_1 are the adjustment parameters. However, this approach did not determine the standard errors of the restricted parameters.

Modelling the farmer source of inputs and efficiency relationship

The study examined how the source of cotton inputs indicators affected the technical efficiency of cotton farmers in the three selected provinces of Zimbabwe: while these indicators could be included in the 3-stage model, the analysis does not offer the flexibility for modelling data with heterogeneous conditional distributions. Moreover, some sources of input indicators are highly correlated with other explanatory factors that lead to biased results. To conduct the analysis, a quantile regression was used to estimate the impact of cotton production input source effects at 25th, 50th and 75th percentiles. A quantile regression models the relationship between the efficiency and source of input indicators using a conditional quantile, evaluating the specific impact of these indicators on different groups of farms clustered on their level of efficiency. We hypothesised that the impact of inputs source indicators on the cotton farm's technical efficiency will vary, depending on how far each farm is from the production frontier. This model was mathematically expressed as follows:

$$TE_k = \zeta_k \beta_\theta + u_{\theta k} \quad (\text{Eqn. 8})$$

$$Q_k(TE_{k/\zeta}) = \zeta_k \beta_0 \quad \text{and} \quad Q_\theta(u_{k/\zeta}) = 0$$

Where, β_θ and ζ_k are $k \times 1$ vector, ζ is a vector of covariates, $Q_\theta(TE_{k/\zeta})$ is the θ^{th} conditional quantile of TE given ζ and TE is the $N \times 1$ vector, which was obtained from the 3-stage model. β_θ was obtained from the following expression:

$$\text{minimise } \sum_k |TE_{\theta k} - \sum_l \beta_{\theta l} \zeta_{kl}|,$$

where $TE_{\theta k}$ is the TE of farm k at quantile θ ($k=1, n$); ζ_{kl} is the covariate l for farmer k and $\beta_{\theta l}$ is the impact of covariate l on TE at quantile θ .

In this study, two types of knowledge indicators were considered as noted in Manevska-Tasevska (2013): formal (e.g years of master farmer training, level of education) and non-formal (e.g participation in farmer groups) knowledge. The study also factored the agricultural experience of the farmer. Additionally, the formal education variable was interacted with farm size and off-the farm work variables to express the managerial and coordination capability of the farming household.

RESULTS AND DISCUSSION

After sampling the farmers, we observed that all (1080 farmers) were under the government aided input scheme so no self-funded and contract with another organisation. This indicated that by the time of data collection COTTCO enjoyed monopoly in cotton production. In this regard, the way how cotton was grown in the three provinces was approximately similar since the COTTCO had a uniform format in providing extension services to its registered farmers.

Description of the variables

The descriptive statistics of cotton yields, inputs, and the explanatory variables used in the analysis are shown in table 1. The output is the harvested amount of seed cotton which is measured in tons. A preliminary production model with five conventional inputs: cotton land area ($\times 3$), labour ($\times 3$), fertilizers ($\times 2$), pesticides ($\times 5$), and seeds ($\times 5$). Seed input variable was dropped from the final model, because of similar seeding rates. The land input variable also caused a problem with the model, as it was highly correlated with the other variables.

Table 1: Descriptive statistics

	Units	Khorem (n = 1080 observations)			
		Mean	SD	Min.	Max
Output variable					
Yield	t ha ⁻¹	0.84	0.21	0.4	2.0
Production variables					
Labour	Person.day ⁻¹ ha ⁻¹	4.2	1.03	0.25	0.8.0
Fertilizer (Basal & Top dressing)	Kg ha ⁻¹	150.0	40.0	100.0	400.0
Seeds	Kg ha ⁻¹	6.2	2.4	1.2	8.0
Pesticides	Kg ha ⁻¹	16.4	10.4	5.7	12.0
Land	Kg ha ⁻¹	0.56	5.2	0.50	3.1
Farm Characteristics					
Farm size (Fsize)	Ha	0.25	3.7	0.25	2.1
Land capability class (Lcapclass)	index (I-VIII)	56.8	12.1	29	75
Crop diversification index (Dindex)	index (0≤)	0.26	0.36	0	1.45
Soil type (Stype)	Dummy	0.50	0.48	0	1
Socio-demographic and institutional characteristics					
Involved in off-farm work (offwork)	Dummy	0.34	0.53	0	1
Dependency ratio (Dratio)	Ratio	1.0	1.11	0.2	9
Satisfaction with Cottco services	Dummy	0.62	0.47	0	1

(CoService)					
Access to inputs (Ainputs)	Dummy	0.82	0.39	0	1
Knowledge indicators					
Cotton production experience (<i>cpxp</i>)	Years	6.1	8.7	1.2	40
Graduated from college (<i>Edu1</i>)	Dummy	0.10	0.62	0	1
Graduated from high school (<i>Edu2</i>)	Dummy	0.21	0.36	0	1
Completed only primary school (<i>Edu3</i>)	Dummy	0.43	0.41	0	1
No formal school (<i>Edu4</i>)	Dummy	0.56	0.45	0	1
Educational background (<i>Edb</i>)	Dummy	0.58	0.50	0	1
Attendance of trainings (<i>Attrain</i>)	Frequency	5.33	1.20	2	8
Agronomic practices					
Reliable rainfall (<i>Rrain</i>)	Dummy	0.29	12.0	0.2	36
Planting time (<i>Ptime</i>)	Dummy	0.45	2.3	0	1
Land preparation (<i>Landprep</i>)	Dummy	0.30	0.1	0	0
Weeding frequency (<i>weedfrq</i>)	Frequency	3.1	1.4	2.8	4.0
Spraying frequency (<i>sprayfrq</i>)	Frequency	5.1	2.0	3.0	6.2

^aThe study used the Shannon diversity index to capture farmer's crop diversity.

Shannon diversity index = $\sum_{j=1} (P_i \times \ln P_i)$ where j = stands for number of crops, P_i = the proportion of the area used for a particular crop and \ln = natural logarithm- it is 0 if the farmer grows only one crop.

^bRatio of family dependents aged <18 and >75 years compared to the number of family adults who are working age.

In this study, dataset was normalised as follows:

$$\text{normalised dataset} = \frac{\text{inputs and outputs}}{\text{land input variable}}$$

Labour input variable is in person-days and one working day is equal to 6 hours. Our final model has only pre-harvest labour that includes both the family and hired labour, this was due to the incurred inconsistency during data collection related to the harvest and post-harvest period. It is argued that labour activities during these periods affects yield on a small scale but not on the production frontier. In this research, the nitrogen fertilizer was calculated from the fertilizer application data, considering the proportion of nitrogen in each fertilizer type. We noted that the farmers used five types of fertilizers for cotton production. Explanatory variables were divided into four categories: farm aspects, socio-demographic and institutional characteristics, knowledge indicators and agronomic practices (Table 1).

Farms in the sample have a land capability class of VIII, which indicates that the quality of the lands used for cotton production by the farmers is low. The land capability class considers the soil potential productivity values indexed from I to VIII. The average farm size was 0.25 ha, and the farmers had an average of 6 years farming experience. On average, 82% of the farmers indicated easy access to cotton inputs and 34% were involved in off-the farm activities. Approximately 56% farmers did not have formal education, 29% highlighted that the rainfall had been reliable for cotton production and only 45% showed that the planting time was good. This suggests that the onset of the rainfall has been inconsistent in the sampled districts.

Production frontier analysis

The research applied the R package 'frontier' to estimate the unrestricted (traditional) and restricted SFM. The quadprog was used to calculate the minimum distance (Turlach and Weingessel, 2011). Results for each model every stage are shown in Table 2. In the first stage analysis, the input variables included pesticides, labour and fertilizer (both basal and top dressing), showing a significant ($P=0.05$) and positive relationship with seed cotton yield. However, some of the interactions were significant, indicating signs of non-linearity in the structure of production. A theoretical consistency was achieved by imposing monotonicity. As a result of this imposed restriction, a small change was noted in the model coefficients (Diff. labelled column) estimated in the 1st and 2nd stages (Table 2). This observed change is less than $1 \times$ standard error of the 1st step estimation (Diff/SE labelled column) (Table 2).

Table 2: Comparison of coefficients obtained from three stages

	1 st step		2 nd Step			3 rd Step		
		MLE Coeff.	SE		MDE Coeff.	Diff.	Diff/SE	Adj. Coeff.
Constant	B ₀	2.321	0.204	***	1.157	-0.163	-0.606	2.104
Ln(Pesticides)	B ₁	0.620	0.174	**	0.513	-0.029	-0.129	0.600
Ln(Labour)	B ₂	0.123	0.103	***	0.173	-0.078	-0.284	0.121
Ln(Fertilizer)	B ₃	0.689	0.218	**	0.701	-0.228	-0.651	0.652
Ln(Pesticides)*Ln(Pesticides)	B ₁₁	0.215	0.110	NS	0.133	-0.015	-0.060	0.202
Ln(Pesticides)*Ln(Labour)	B ₁₂	0.048	0.023	**	0.026	-0.023	-0.074	0.034
Ln(Pesticides)*Ln(Fertilizer)	B ₁₃	0.132	0.554	*	0.104	-0.018	-0.068	0.131
Ln(Labour)*Ln(Labour)	B ₂₂	-0.094	0.037	*	-0.045	0.032	0.123	-0.081
Ln(Labour)* Ln(Fertilizer)	B ₂₃	0.029	0.061	NS	0.030	-0.019	-0.056	0.025
Ln(Fertilizer)*Ln(Fertilizer)	B ₃₃	0.400	0.135	*	0.136	-0.129	-0.426	0.312

The final estimates (Adj. Coeff. labelled column) indicated the restricted coefficients after modifying the production frontier with the ω_0 and ω_1 coefficients. The production elasticity relating to labour was 0.13, which is higher than the elasticities relating to the fertilizer and pesticides. The pesticides and fertilizer production elasticities ranged between 0.06 and 0.08.

In this study, three hypotheses were tested in relation to the specification of the model using a likelihood ratio test. The choice of the Cobb-Douglas (C-D) versus the translog functional form were tested. Results rejected the C-D as the preferred functional form (H_0), suggesting that the translog functional form was more appropriate. In the second hypothesis, technical inefficiency (TE) was tested where the H_0 had no inefficiency effect. The H_0 was also rejected, indicating the joint effect of the exploratory factors significantly contributing to the TE. The last hypothesis was the restricted versus unrestricted model. The results failed to reject that the restricted frontier model was the preferred model. Suggesting that monotonicity as an important property that should be seriously considered in frontier modelling.

Table 3: Results from unrestricted and restricted models

Initial estimates					Final estimates		
Coefficient		SE			Coefficient		SE
Final Stage							
Intercept					0.032	NS	0.072
<i>LcFitted.</i>					0.98	***	0.055
Inefficiency Effects Model							
Constant	0.436	***	0.208		0.457	***	0.041
<i>Lcapclass.</i>	-0.001	NS	0.218		-0.001	NS	0.002
<i>Fsize.</i>	-0.002	***	0.106		-0.002	***	0.001
<i>Weedfreq.</i>	-0.022	***	0.103		-0.023	***	0.004
<i>Dindex.</i>	-0.011	NS	0.032		-0.012	NS	0.023
<i>Offwork.</i>	0.025	NS	0.061		0.025	*	0.012
<i>Edb.</i>	-0.060	***	0.044		-0.054	***	0.018
<i>Dratio.</i>	0.004	NS	0.162		0.002	NS	0.007
<i>Landprep.</i>	0.005	NS	0.166		0.003	NS	0.008
<i>Stype.</i>	0.041	**	0.001		0.040	***	0.012
<i>Sprayfrq.</i>	-0.041	**	0.001		0.003	**	0.017

<i>Rrain.</i>	-0.012	***	0.003		-0.001	***	0.011
<i>Attrain.</i>	-0.030	**	0.001		-0.007	***	0.013
<i>Epxp.</i>	0.002	**	0.014		0.003	**	0.011
<i>Ainputs.</i>	-0.101	*	0.010		-0.001	*	0.012
<i>CoService.</i>	-0.013	NS	0.011		-0.021	NS	0.018
Efficiency Diagnostics							
SigmaSq	0.007	***	0.010		0.008	***	0.001
Gamma(γ)	0.912	***	0.004		0.902	***	0.013

The variance parameter (SigmaSq) is positive and statistically significant at the 5% level showing the goodness of the composite error's distributional assumptions (Table 3). Gamma (γ) is equal to 0.91 and significant at 1%, therefore the technical inefficiency effect describes a considerable fraction of the total variation in the data. The final restricted model met the monotonicity condition for all observations and variables and is quasiconcave at 96.0% of the observations. The imposition of the monotonicity improved the significance of some of the variables in the final model (Table 3). The off-farm work variable (*offwork*) became significant at $P=0.10$ and for the soil type (*stype*), attending training (*Attrain*) and experience in cotton production (*Epxp*) the significance level increased from 5% to 1% (Table 3). The intercept was not significant at all the p-values and the scaling coefficient is approximately equal to 1, indicating that the model was highly robust. Considering that the highest TE is obtained at a score of 1.0, our model results indicated that there was still room for efficiency improvements with the farmers' existing resources. Therefore, the results suggest that farms could increase their cotton production without adding more inputs under the current presidential input scheme.

Inefficiency effects analysis

The inefficiency effects model (Eqn.8) included 15 variables (Table 3). The model used technical inefficiency as a dependent variable, just for convenience, but the study used TE in explaining the outcomes resultantly, the sign of the explanatory variables is changed in the discussion. The farm size variable (*fsize*), has a positive and significant ($p=0.001$) relationship with TE. This showed that the farm size had an effect on resource utilization.

The results showed that the reliable rainfall dummy (*Rrain*) had a positive and significant result with TE. This means that having reliable rain during the cotton season enabled farmers to be

more efficient as the agronomic activities would be done on time hence improved yields. However, this finding should be carefully interpreted, because some farmers may not receive reliable rainfall because of the varying agro-ecological regions. The three provinces have different climatic characteristics where some farmers are located in naturally dry areas where some are in relatively wetter areas. Battese and Coelli (1995) and Tian and Wan (2000) also noted similar results on farm technical efficiencies which were influenced by characteristics of the area.

The increased number of weeding activities (*Weedfreq*) and spraying frequency (*Sprayfreq*) positively affected the TE of the cotton farms. Mathijs and Vranken (2001) emphasised that weeding are major challenges that can be caused by poor agronomic practices (e.g. lack of crop rotations). Applying herbicides is not common, because of the high costs associated plus the chemicals can decrease the quality of the cotton. Hence, the farmers resort to manual weeding done by farm family members but hired labour on larger cotton areas. The involvement in off-farm work dummy (*Offwork*) negatively affected the TE. As expected, the farmers who are involved in off-farm activities had lower efficiencies in cotton production as these farmers were sharing their time between farming and other off-farm activities. Tschirley et al. (2010) observed that farming is not the only source of income for rural farmers. Therefore, although farmers can invest their additional income in cotton production, time spent on off-farm work might have an efficiency-reducing effect.

Quantile analysis: importance of knowledge indicators

The results indicated that farmers who have a university education (*Educ1*) were most efficient in resource utilization at $p=0.05$ in the 25th and 50th TE percentiles (Table 4). This showed that obtaining a higher education had a positive effect on TE. Hence, emphasised the significance of specialized knowledge required for better farming. To support this argument, the study also associated farm efficiency with agriculture related education (*Edb*). The results indicated that the educational background of the farmer had a bearing on efficiency improvements. The relationship between those who have received an agricultural education and efficiency are highly significant. A possible reason for this could be that farmers with an educational background in agriculture are able to use agronomic practices on time and in an effective and efficient way. These knowledgeable farmers know the specifics of farming and can easily adjust to different situations, depending on the available resources. Limited studies using this variable in their analysis did not find any significant relationship (Mathijs and Vranken, 2001; Manevska-Tasevska, 2013). The results are however contradicting Reimers and Klasen (2013), who concluded that primary and secondary education were more relevant in farming than higher education. In support of this view, Mathijs and Vranken (2001) noted that, in other countries,

schooling was effective in transferring knowledge, but was insignificant in other countries and shapes no skills.

The study used the interaction term between university (*Educ1*) and college education (*Educ2*) with off farm-work (*Offwork*) and found statistically significant results, regardless of the different quantile groups (Table 4). The effect was strongest for those who have a university education. This showed that the highly educated farmers had no capacity to handle on and off-farm activities, which negatively affected the resource utilization. This further supported that better time allocation and a physical coordination of daily farm activities are important in resource utilization. Our results indicated the importance of the knowledge gained from attending training (*Attrain*), which had a significant positive influence on efficiency in all of the quantiles.

Manevska-Tasevska (2013) noted a positive relationship between non-formal education and TE. This suggests the importance for agricultural training programs that assist farmers in upgrading farming knowledge and obtain updated information about new farming technologies. Based on this observation, Musara et al. (2018) advocated for the establishment of formal extension services so as to help farmers in improving their yields. The government of Zimbabwe has attempted to establish such formal training together with some non-governmental organisations. However, the uptake of such services is minimal and should be increased among the smallholder farmers. Manevska-Tasevska (2013) also found a negative relationship on the extension services uptake and explained it by the fact that more experienced farmers were more resistant to new technologies and practices.

The agricultural experience (*Epxp*) of the cotton farmers was significant at the 25th TE percentile and statistically not significant in the other two quantiles (Table 4). This suggested that farming experience does not contribute to achieving higher efficiency values. While cotton is grown for many years and farmers gained extensive experience in its production, the research showed that acquired knowledge is not enough to increase cotton yields to the expected levels. The interaction term between college education (*Educ2*) and farm size (*Fsize*) has been introduced to explore the farmer's managerial ability to handle work at large scale farms. It was significant at $p=0.05$ level in the 25th TE quantile and significant at $p=0.10$ level in the 50th and 75th TE quantiles (Table 4). This showed that obtaining a formal education is not sufficient enough to achieve higher efficiency hence, achieving higher efficiency requires additional training and managerial skills from farmers.

Table 4: Comparison of coefficients obtained from three stages

	0.25				0.50				0.75		
	Coef.	Standard error			Coef.	Standard error			Coef.	Standard error	
Attrain	0.021	0.004	*		0.023	0.004	*		0.016	0.005	*
Epxp	0.001	0.001	**		0.002	0.001	NS		0.002	0.002	NS
Edu1	0.045	0.019	**		0.045	0.020	**		0.048	0.027	**
Edu3	0.022	0.030	NS		0.013	0.019	NS		0.026	0.027	NS
Edb	0.053	0.017	***		0.080	0.011	***		0.053	0.018	*
Educ*Fsize	0.001	0.001	***		0.001	0.001	***		0.003	0.015	*
Offwork*edu1	-0.064	0.031	***		-0.062	0.025	***		-0.052	0.029	***
Offwork*edu2	-0.032	0.020	***		-0.041	0.017	***		-0.013	0.021	**
_cons	0.733	0.033	**		0.550	0.030	**		0.546	0.040	**

CONCLUSIONS

We used current methodological developments to evaluate the efficiency of cotton farms in three major cotton producing provinces of Zimbabwe. Since there was little research on farm efficiency in Zimbabwe, this study filled a void in the literature by developing a theoretically consistent model and applying it within a complex socioeconomic environment. It highlights the importance of monotonicity and quasiconcavity violations, which can cause biased efficiency results. The study showed some factors which significantly ($P=0.05$) influence farmers' resource use abilities. One of the significant factors aligned to efficiency is the off-farm work variable. Considering that growing cotton requires full concentration throughout the year, farmers who are involved in off-farm work have lower efficiency. This is especially true for those farmers with sound tertiary education e.g university and college educations because they will be employed elsewhere. The results also pointed to some other variables that improved TE, these included access to reliable rainfall, frequency of weeding, application of fertilizers, spraying frequency, and farm size. Results indicated that farmers' knowledge attributes can potentially influence the farmers' resource use pattern. Formal education and attending agricultural training were associated with improved efficiency. However, results showed that having basic education was

not sufficient to achieve higher efficiency in cotton production. Based on this, a state policy to establish colleges in rural and remote areas is required so as to achieve significant cotton production in the future.

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COMPETING INTERESTS

The authors declare that they have no competing interests

DATA AVAILABILITY STATEMENT

The raw data used to support the findings of this study are available from the corresponding author upon request.

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