The Impact of Drought on Technical Efficiency of Smallholder Farmers in Hurungwe, Zimbabwe

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Abstract

Increasing drought frequencies due to climate change, pose a serious threat to rain-fed farmers in rural Africa where the policy thrust points to improving efficiency of these farmers. This article uses cross sectional data collected from 411 randomly selected farmers and applies the stochastic frontier method (SFM) to investigate the extent to which drought influences technical efficiency of smallholder farmers in Hurungwe, Zimbabwe. First, technical efficiency of smallholder farmers is computed using the SFM. Second, two groups of farmers, one from drought prone areas and the other from wet ecological zones, are compared with regards to their technical efficiency levels using a binary covariate which classifies the farmers into two groups. The findings show a low level of technical efficiency of maize farmers in Hurungwe. The average technical efficiency level is 45.3%. Drought is found to be detrimental to technical efficiency, with farmers in drought prone areas being 19% less efficient than those in wet ecological zones given their different demographic characteristics. Drought experience, education, farming experience, modern methods of forecasting and access to credit contribute positively to technical efficiency. The findings point to the need for improving technical efficiency of maize farmers. Negative effects of drought on efficiency could be reduced by building irrigation infrastructure in drought prone areas or by reallocating farmers to wet ecological areas. In addition to construction of irrigation infrastructure and reallocation of farmers, we also recommend increased education support, financial inclusion of rural farmers through the development of rural financial institutions and publication of drought related information for farmers' consumption.

Key words: **Farmers, Drought, Technical efficiency, Hurungwe**
JEL: D24; Q12; Q18

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1. Introduction

Agriculture has remained the backbone of Zimbabwe's economy, in terms of both employment creation and export production, with smallholder farmers playing a critical role in agricultural production. Over 65% of the population live in rural areas and their livelihoods depend on agriculture (Anseeuw *et al*., 2012 and Juana and Mabugu, 2005). Improving productivity of smallholder farmers is therefore vital not only to poverty reduction but also to the development of the economy. The question is: "how can technical efficiency of these smallholder farmers be improved?" The measurement of technical efficiency is well documented in literature but the question on whether dry weather conditions generate technical efficiency loss remains unsettled. For example, Tian and Wan (2000) found no evidence of a significant relationship between wet weather and technical efficiency in China. But Tasnim *et al*. (2014), Lemba *et al*. (2012) and Makki *et al*. (2012) established otherwise. Lemba, *et al*. (*Ibid*) established that farmers with irrigation were more efficient than those without in the dry lands of Kenya. In Zimbabwe where resettlement of farmers is ongoing, it is paramount to investigate whether farmers in wetter ecological zones are more efficient than those in drier zones.

Food insecurity has continued to haunt Africa despite the fact that over 73% of the rural population are involved in farming (Odulaja and Kiros, 1996). La-Anyame (1985) argues that agricultural growth in Africa has been lagging behind population growth thereby putting pressure on food demand. For example, in Zimbabwe imports of maize have become persistent over the past decade in spite of a growing population of farmers in the rural areas due to unemployment (Masunda and Chiweshe, 2015 and Anseeuw *et al*., 2012). This suggests that improving efficiency of smallholder farmers should be the policy thrust for interventions in rural Zimbabwe. Since independence, the Government of Zimbabwe has continued to support the agricultural sector in order to improve productivity. Anseeuw *et al*. (2012) argues that government actions promoted the development of smallholder farming through land reforms, input subsidies, irrigation infrastructure and animal disease control, among others. However, a number of the formulated agricultural policies were not implemented. For example, the Agricultural Mission Statement Strategy Framework and Action Plan, 2007–2011 was never adopted because the government was preoccupied with land reform and resettlement programmes (Anseeuw *et al*., 2012).

Most studies on efficiency in Zimbabwe have concentrated on the impact of government policies on technical efficiency of farmers (Musara *et al*., 2012; Mazvimavi *et al*., 2012; Chisango and Obi, 2010 and Kapuya *et al*., 2010) and on measuring technical efficiency of farmers (Masunda and Chiweshe, 2015 and Dube and Guveya, 2012). First, these studies have overlooked the potential impact of climate variables such as drought on productivity of smallholder farmers. Second, improving maize production is critical for food security in Zimbabwe but a majority of studies done on efficiency in Zimbabwe is on other crops. Third, despite being one of the major maize-producing districts in Zimbabwe henceforth critical for food security in the country, no attempt has been made to study efficiency of maize farmers in Hurungwe district. Studies that have attempted to estimate drought cost in terms of reduced agricultural output are national level studies (Gbegbelegbe *et al*., 2014; Pauw *et al*., 2011; Arndt *et al*., 2011; Beniston, 2007 and Mano and Nhemachena, 2006). Macro studies, however fail to provide useful community level information for policy makers to enable them to influence community development because of aggregation. Understanding the impact of dry weather conditions on technical efficiency of smallholder farmers at a community level is vital for both farmers and policy makers in order to increase maize output in a changing climate. Farmers need to prepare for options to counter drought impact on their productivity while policy makers use the information when making decisions such as resettling people and making disaster prevention strategies.

It is against this background that this article examines efficiency losses/gains from varying weather conditions and the relationship between smallholder farmers' characteristics and technical efficiency. Specifically, the article measures technical efficiency of smallholder farmers in Hurungwe and examines the drivers of technical efficiency levels of farmers with particular attention given to drought impact. The rest of the article is organised as follows: Section 2 reviews efficiency literature. Section 3 explains the methodology, while section 4 presents the results. Finally, section 5 concludes and proffers some policy implications.

2. Literature Survey

In economic literature, technical efficiency is measured using two main techniques, namely, parametric and non-parametric. In non-parametric method, no functional form is imposed on the production frontier and nothing is assumed on the error term. A linear programming approach is applied in non-parametric methods and the most popular one is the Data Envelopment Analysis (DEA). On the other hand, researchers (Battese and Corra, 1977 and Aigner, *et al*., 1977) developed a parametric Stochastic Frontier Model (SFM) which imposes a functional form on the production function and makes assumptions about the data. A number of researchers have trailed these techniques of measuring technical efficiency. Chirwa (2007) argues that despite the importance of measuring technical efficiency of farmers in Africa, very little has been done in this area. More work on technical efficiency of farmers has however been done outside Africa.

The Stochastic Frontier Approach (SFA) has been the most commonly used approach in measuring technical efficiency of farmers (Mazvimavi *et al*., 2012; Chisango and Obi, 2010; Chirwa, 2007; Battese and Coelli, 1995 and Ekanayake and Jayasuriya, 1987). In Zimbabwe, Chisango and Obi (2010) applied this approach to investigate the impact of mechanization and Fast Track Land Reform Programme (FTLRP) on efficiency of Bindura farmers. The same technique was applied by Mazvimavi *et al*. (2012) to compare technical efficiency between conservative and conventional agriculture. In most Asian countries, the SFA was applied to measure technical efficiency of rice farmers. The most popular characteristic of these studies is that they all focused on measuring efficiency. While these studies have done a considerable work on producing efficiency scores, more work needs to be done for different regions of Africa.

There is vast literature worldwide on the measurement of technical efficiency but little attempt has been made to examine the determinants of technical efficiency of maize farmers in Zimbabwe despite the critical role played by smallholder maize farmers. A diversity of efficiency determinants have been identified in a number of studies using either the SFA or the DEA. The most common factors identified are education, credit access, farm size, seed quality, cropping intensity and gender, among others (Masunda and Chiweshe, 2015; Ibrahim *et al*., 2014; Tasnim *et al*., 2014; Mapemba *et al*., 2013; Makki *et al*., 2012; Okon *et al*., 2010; Singh *et al*., 2009 and Tian and Wan, 2000). Despite some research on the impact of dry weather conditions on technical efficiency (Ibrahim *et al*., 2014; Ogada *et al*., 2014; Tasnim *et al*., 2014; Makki *et al*., 2012 and Tian and Wan, 2000), the findings on how weather conditions influence farmers' technical efficiency are still inconclusive. For example, Ibrahim *et al*. (2014) and Makki *et al*. (2012) established that drought/dry weather conditions reduce technical efficiency of farmers while Tian and Wan (2000) established otherwise.

Ibrahim *et al*. (2014) applied the stochastic frontier approach to examine technical efficiency of at least 40 maize farmers across agro-ecological zones of Northern Nigeria. The results indicate a positive relationship between technical efficiency and education, access to credit, household size, market variables and farm size. Farmers in wetter agro ecological zones were however found to be more technically efficient than those in drier zones. Using the same approach, Makki *et al*. (2012) established similar positive association between technical efficiency and agricultural inputs (which included land, fertilizer, labour, pesticides and wet weather conditions) of local rice farmers in Indonesia. On the contrary, Tian and Wan (2000) found wet weather conditions/irrigation to be an insignificant determinant of technical efficiency of grain farmers in China. Many studies identified education as a significant determinant of technical efficiency (Masunda and Chiweshe, 2015; Ibrahim *et al*., 2014; Mapemba *et al*., 2013; Makki *et al*., 2012 and Singh *et al*., 2009). Tian and Wan (2000) however identified this positive association to hold only between education and technical efficiency of maize and wheat farmers but not for rice farmers. Singh *et al*. (2009) even established a non-existent association between education and farm-specific technical efficiency in Tripura, India.

While there is a sensible level of consistency in the methods used to measure technical efficiency and its determinants, the impact of some determinants on technical efficiency still remains ambiguous. For instance, on one hand some researchers established a negative association between farm size and technical efficiency (Okon *et al*., 2010; O'Neill *et al*., 2001 and Herdt and Mandac, 1981) while on the other hand some found larger farms to be more efficient than smaller farms (Ogada *et al*., 2014; Igliori, 2005; Thirtle and Holding, 2003 and Sherlund *et al*., 2002). Other studies, for example, Mochebelele and Winter-Nelson (2000) established a non-existent relationship between farm size and technical efficiency. In some cases the impact of farm size on technical efficiency depends on the crop type (Tian and Wan, 2000). According to Tian and Wan (*Ibid*), technical efficiency was only positively associated with average farm size for rice farmers in China but the association was negative for wheat farmers. The fragility of these findings as also noted by Townsend *et al*. (1998) indicates heterogeneity of determinants coefficients which require area-specific research.

The study of technical efficiency is based on the production function and hence the quality of inputs is a key determinant of technical efficiency. Previous studies have however taken production inputs into consideration in the modeling of technical efficiency but with little or no emphasis on the quality of natural inputs such as climate factors (Ibrahim *et al*., 2014; Mazvimavi *et al*., 2012; Singh *et al*., 2009 and Chirwa, 2007). Weather is an important input in agriculture, hence leaving it when modelling technical efficiency in agriculture may result in non-robust findings. The knowledge of how much efficiency is lost due to dry weather conditions is necessary for the Government when resettling communities and planning for drought relief.

3. Model of Technical Efficiency and Data Issues

This article applies a two-step procedure to examine the impact of drought conditions on technical efficiency of smallholder farmers in Hurungwe. The first phase involves measuring technical efficiency of farmers and the second phase examines how drought and other factors influence technical efficiency of smallholder farmers. The Farrell (1957) and Debreu (1951) approach to measuring technical efficiency is applied in this article. The main advantage of the stochastic frontier model (SFM) over data envelopment analysis (DEA) is that SFM accommodates random variations in catch, that is, SMF is more appropriate when data noise is more likely a problem (Coelli *et al*., 1998). If farmers are 100% technically efficient then they will be producing along the production possibility frontier. A parametric frontier for a cross-sectional production function is presented as:

$$Q_i = f(Z_i, \beta)e^{\varepsilon_i} \tag{1}$$

where Q_i is the observed output of the i^{th} farmer, Z is vector of inputs, β is a vector of slope coefficients and $\varepsilon_i = v_i - u_i$ is a composite error term. The first component of the composite error term, v_i, is assumed to be symmetric and normally distributed and it captures output variation due to factors beyond the farmer's control. The second component, u_i, is one-sided error term capturing inefficiency of the farmer.

Technical efficiency is defined as the ratio of the observed output to maximum possible output, that is:

$$TE_i = \frac{Q_i}{f(Z_i, \beta)} \tag{2}$$

The observed output can be expressed in terms of exponent as:

$$\exp(Q_i) = \exp(Z_i\beta + v_i - u_i) \tag{3}$$

The maximum possible output can be expressed in terms of exponent as:

$$\exp(Z_i\beta + v_i) \tag{4}$$

Substituting equations (3) and (4) into equation (2) we obtain a measure of technical efficiency expressed as:

$$TE_i = \frac{\exp(Z_i\beta + v_i - u_i)}{\exp(Z_i\beta + v_i)} = \exp(-u_i) \tag{5}$$

Equation (5) shows that if u_i is zero then technical efficiency is 100%, that is, the farmer is assumed to be technically efficient (actual output equals the maximum possible output). The following empirical stochastic production function is estimated:

$$\log Q_i = \pi_0 + \pi_1 Lab_i + \pi_2 Seed_i + \pi_3 Fert_i + \pi_4 Ploughs_i + \pi_5 Land_i + v_i - u_i \tag{6}$$

where Q is maize output of the i^{th} farmer, *Lab* is total farm labour, *Seed* and *Fert* are maize seed quantity and fertilizer quantity, respectively, *Ploughs* is the number of ploughs, *Land* is maize hectrage (land devoted to maize) and π_s are the parameters to be estimated. Output is logged because logging it is more log normal. The residuals from equation (6) are used to compute technical efficiency using equation (5) which is then used as a dependent variable in the second phase.

In the second phase, the impact of dry weather conditions on technical efficiency (TE) of smallholder farmers is modelled as follows:

$$TE_i = \lambda_0 + \lambda_1 DS_i + \sum_{k=1}^{K} \phi_k X_{ki} + \varepsilon_i \tag{7}$$

where TE_i is a measure of technical efficiency of farmer *i*, DS_i is a dummy variable which takes a value of 1 if a farmer experiences drought and zero otherwise, *X* is a vector of control variables which include farm size, education, farming experience, gender, age, drought experience, access to credit, extension services and seed quality, λ_0, λ_1 and ϕ are the parameters to be estimated whereas ε is a random disturbance assumed be identically and independently distributed. Equation (7) is one of the two ways of displaying drought impact on technical efficiency of farmers. One way is to recognize drought as a condition of abnormally low precipitation and then use rainfall amount as an input in the production function of farmers. This approach is however, applicable where numerical rainfall data is available for each farmer. The absence of disaggregated rainfall data for Zimbabwe at ward level makes this approach inapplicable when studying output and rainfall variability across wards.

In equation (6) a production function of farmers with the usual inputs without rainfall is estimated for all farmers to generate a technical efficiency score (TE_i) for each farmer. Second, given some farmers' characteristics, a theoretical econometric association between weather and technical efficiency can be derived from the following model:

$$E(TE_i|X, DS_i) = X\beta + \lambda_1 DS_i \tag{8}$$

where X is a vector of farmers' characteristics, β is a vector of the coefficients of farmers' characteristics, DS_i is a dummy variable taking a value of 1 if the farmer experiences drought and a value of 0 if a farmer experiences wet weather and λ_1 is the coefficient of a drought shock dummy. Model (8) produces two models, one for farmers experiencing a drought shock and the other for farmers experiencing wet weather conditions. The models are:

$$E(TE_i|X)_{Dry} = X\beta + \lambda_1 \quad (\text{since } DS_i = 1) \tag{9}$$

$$E(TE_i|X)_{Wet} = X\beta \qquad (\text{since } DS_i = 0) \tag{10}$$

Subtracting equation (10) from equation (9) we obtain:

$$\lambda_1 = E(TE_i|X)_{Dry} - E(TE_i|X)_{Wet} \tag{11}$$

Hence the parameter λ_1 measures the difference in average technical efficiency between farmers experiencing wet weather and those experiencing drought and is expected to be negative. It is the magnitude of a loss or a gain in technical efficiency created by weather variability. Farmers experiencing drought are expected to be less efficient than those experiencing wet weather conditions. To remedy the problem of heteroscedastic variances and autocorrelation, equation (7) is estimated using robust standard errors.

The study uses primary data collected in 2015 from a sample of 411 randomly selected farmers in three Wards of Hurungwe district consisting of two groups of farmers, one group from drought prone areas and the other group from wet areas. A multi-stage sampling technique was applied. First, wards were stratified according to agricultural ecological zones (regions IIA, III and IV) and one ward was then randomly selected from each ecological zone. Second, each selected ward was proportionally represented in terms of sample units. Enumeration areas (EAs) within each selected ward were randomly selected and a census was finally carried out within the selected EA. EAs were developed by ZIMSTAT for the 2012 population Census. The sample size for enumeration areas was generated from Cochran (1977)'s formula with an error margin of ±5%.

4. Results and Discussion

The majority (79.3%) of farmers use ploughs and draught power in the production of maize. Only 5.6% of the farmers do not have ploughs and use hoes only. Mechanization is still lagging in the district despite improved incomes from tobacco growing (see Keyser, 2002). About 15.1% of the farmers have mechanized their farms mainly through tractor and water pump acquisitions. Maize is produced on a small scale as indicated by the average tonnage of 2.9 shown in Table 1. However, variations in maize production are very huge with a standard deviation of 4 tonnes. Besides hoes, ploughs, draught power and heavy machinery, the other inputs used in maize production by farmers in Hurungwe include farm land, seed, organic and non-organic fertilizers and labour. The average farm size in the district is 8.7 hectares while farmers set aside an average of only 2.6 hectares for maize production. The mean number of ploughs and draught animals are 1 and 5, respectively (see Table 1).

Farmers in Hurungwe mainly use treated maize seed and non-organic fertilizers. About 93% of farmers use treated maize seed, 82.5% apply non-organic fertilizer, 11.9% use manure, while 5.6% do not use any fertilizer or manure. On average, each maize farmer uses 44.4 kilograms of maize seed and 266.9 kilograms of fertilizer in maize production per growing season. Labour is mostly unpaid family labour. The average labour force is 5 with a standard deviation of 5 workers. There are huge variations in most of the maize inputs used by the farmers except in plough ownership. It is however not surprising to have such huge variations in a rural setting such as Hurungwe where income variations are also huge (see Kinsey *et al*., 1998).

Table 1: Descriptive Statistics of Maize Production

Variable	Observation	Mean	Std. Dev	Minimum	Maximum
Maize output (tonnes)	411	2.9	4	0	35
Farm size (ha)	411	8.7	6.1	1	40
Maize hectrage	411	2.6	1.9	0.5	20
Productivity (tonnes/ha)	411	1.3	1.5	0	11.7
Ploughs	411	1	1	0	20
Oxen	411	5	8	0	100
Labour	411	5	5	1	80
Seed quantity (kg)	411	44.4	35.3	6	250
Fertilizer quantity (kg)	375	266.9	338.4	0	5200

Source: Authors' Compilation

Table 2: Average Production and Productivity According to Ecological Conditions

Characteristic	Drought shock (N=172)	Wet weather (N=239)	Total (N=411)	Difference
Maize output (tonnes)	1.75	3.74	2.9	-1.99***
Productivity (tonnes per ha)	0.76	1.74	1.3	-0.98***
Maize hectrage	2.81	2.41	2.6	0.40**
Farm size	9.50	8.20	8.7	1.30**
Years of schooling	8.27	9.25	8.8	-0.98**

***, ** and * indicate that the difference between farmers experiencing a drought shock and wet weather conditions is statistically significant at 1, 5 and 10 percent level, respectively. Difference in means were tested using t-tests for equality of means and Levene's test for equality of variances

Source: Authors' Compilation

Table 2 shows average maize production and productivity in dry and wet zones. The statistics show some expected findings, that is, they demonstrate that the average maize output for farmers experiencing drought is lower than that of those experiencing wet weather conditions. The difference in mean output is 1.99 tonnes and is statistically significant at 1% level. Similarly, farmers experiencing droughts have a lower average productivity level as compared to those experiencing wet weather conditions. On average, farmers experiencing droughts produce 0.98 tonnes per hectare less than those experiencing wet weather conditions. The difference in tonnage per hectare between these two groups of farmers is statistically significant at 1% level. Despite having higher productivity and output, farmers experiencing wet weather conditions have smaller farms on average and their mean maize hectrage is also smaller than those in drought-prone areas. The difference in average farm size between the two groups of farmers is statistically significant at 5% level. The estimated production function is presented in Table 3.

Table 3: Determinants of Maize Production

	(1)	(2)	(3)
Variables	log(Maize output)	log(Maize output)	log(Maize output)
Farm size	-0.00350	-0.00449	
	(0.0112)	(0.0112)	
Maize hectrage	-0.0757*	-0.0739*	-0.0828**
	(0.0441)	(0.0441)	(0.0382)
Oxen	0.00683		
	(0.00916)		
Ploughs	0.147**	0.175***	0.173***
	(0.0604)	(0.0469)	(0.0465)
Seed quantity	0.00458*	0.00440*	0.00444*
	(0.00246)	(0.00245)	(0.00244)
Fertilizer quantity	0.000674***	0.000680***	0.000665***
	(0.000189)	(0.000189)	(0.000185)
Labour	0.0407***	0.0420***	0.0406***
	(0.0131)	(0.0130)	(0.0125)
lnsigma2v	0.0348	0.0364	0.0368

lnsigma2u	-29.6875	-29.5443	-28.1489
sigma v	1.01753	1.01834	1.018579
sigma u	0.0000004	0.000000384	0.00000077
sigma2	1.035368	1.037019	1.037504
lambda	0.0000004	0.000000377	0.00000076
Observations	352	352	352

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' Compilation

The findings from the estimated production functions presented in Table 3 suggest a production curve that starts from the origin. Inputs which are statistically significant in model (1) remain statistically significant in the other two models demonstrating a reasonable degree of reliability and robustness of the models. The results show that, ploughs, labour, maize hectrage, seed quantity and fertilizer are the major factors explaining variability of maize output in Hurungwe. The coefficients of ploughs, fertilizer quantity and labour are statistically significant at 1% level while that of seed quantity is weakly significant at 10% level. The effect of fertilizer on maize output is however very small; a 1% increase in fertilizer increases maize output by only 0.06% in all three models. Returns to increasing fertilizer application in the district are not much. Variations in seed quantity have also a small impact on maize output. A percentage increase in seed quantity increases maize output by less than 0.5%. This finding however support that farmers are applying the recommended quantity of maize seed per hectare hence no benefits from further increases in seed quantity.

Labour and farming equipment such as ploughs however play a critical role in maize production in Zimbabwe. Increasing labour by 1% will increase output by about 4% and a percentage increase in ploughs will increase maize output by 15 to 18% (see results in Table 3). Despite having a weak statistically significant coefficient in the first two models, (1) and (2), maize output is negatively associated with maize hectrage. A percentage increase in maize hectrage reduces maize output by 8.3%. This suggests that large maize farms are less productive. This finding is similar to results established by Okon *et al*. (2010) and O'Neill *et al*. (2001) in Nigeria and Ireland, respectively.

The stochastic frontier results show that a majority (51.3%) of Hurungwe farmers are technically inefficient, that is, they have technical efficiency scores which are less than 50%. Only 2.9% of the farmers had a technical efficiency score exceeding 80%. Table 4 illustrates the proportion of farmers in different groups of technical efficiency levels. The average level of technical efficiency in Hurungwe is 45.3% with a minimum of 1.6% and a maximum of 88.5%. The mean technical efficiency for farmers experiencing drought is 34.5% while those experiencing wet weather conditions have a higher mean technical efficiency of 51.9%. The difference between the average technical efficiency levels of the two groups of farmers is 17.4% and is statistically significant at 1%. A mean technical efficiency level of only 45.3% for all farmers is very low suggesting a considerable room to improve maize production. However, such low efficient levels are common in developing countries. For example, Chiona *et al*. (2014) established that 14% of the farmers in the Central province of Zambia had a technical efficiency of less than 30%. In Zimbabwe, Dube and Guveya (2012) established that tea growers had a technical efficiency level ranging from 37% to 100% but Mazvimavi *et al*. (2012) found two thirds of the farmers under conservative agriculture having efficient scores in the 60-80% range.

Table 4: Proportion of Farmers in Different Categories of Technical Efficiency

Technical efficiency score	Number of farmers	Percentage
<50	211	51.3
50-60	80	19.5
61-70	83	20.2
71-80	25	6.1
>80	12	2.9
Total	411	100.00

The three variants of the determinants of technical efficiency model presented in Table 5 consistently provide similar statistically significant explanatory variables. This indicates a high degree of model reliability and robustness. The model explains about 85% of the variation in technical efficiency of smallholder farmers in Zimbabwe. The findings reveal that technical efficiency is 19% lower for farmers experiencing drought in the district, that is, an average of 19% of farmers' technical efficiency in Hurungwe is lost due to droughts. The coefficient of drought shock is negative and statistically significant at 1% level. The farmers' incentive to work hard is reduced by persistent droughts. Some farmers may choose to stay home rather than wasting their labour hours if they anticipate droughts. Under such circumstances, output of maize from a given set of inputs may be comparably lower than what the farmers can possibly achieve with the same set of inputs in the absence drought-induced reluctance. Similar findings that droughts reduce farmers' efficiency levels were established by Ibrahim *et al*. (2014) and Makki *et al*. (2012) in Nigeria and Indonesia, respectively. The findings point to an important policy implication that the government's 2030 targets of eliminating poverty and improve food security may not be achieved if nothing is done to mitigate drought impacts.

Despite the negative consequence of drought on farmers' technical efficiency levels, increased drought experience helps farmers to adapt and improve their efficiency levels. The results portray a strong positive association between drought experience and technical efficiency. A year increase in the number of droughts experienced by the farmer increases the farmer's technical efficiency by an average of about 5%. Farmers who have encountered several droughts in their life span are likely to apply extra effort in maize production if they anticipate a drought. As noted by Kinsey *et al*. (1998), improved knowledge of droughts by farmers helps them devise adaptive measures and strategies to counter droughts such as early planting and use of short season varieties. Adaptation is hence critical to improving agricultural productivity in a changing climate (Arndt *et al*., 2011 and Mano and Nhemachena, 2006).

Table 5: Determinants of Technical Efficiency of Maize Farmers

Variables	(1) Technical efficiency	(2) Technical efficiency	(3) Technical efficiency
Drought shock	-0.185***	-0.185***	-0.189***
	(0.0196)	(0.0196)	(0.0197)
Farm size	0.0159***	0.0162***	0.0165***
	(0.00429)	(0.00424)	(0.00423)
Gender	0.0116		
	(0.0259)		
Experience	0.00221**	0.00231***	0.00219**
	(0.000896)	(0.000861)	(0.000862)
Farmer education	0.0149***	0.0154***	0.0137***
	(0.00287)	(0.00268)	(0.00285)
Forecast			0.0383*
			(0.0224)
Credit access	0.0806***	0.0825***	0.0768***

	(0.0264)	(0.0226)	(0.0230)
Extension	0.000792	0.000760	0.000717
	(0.000521)	(0.000511)	(0.000511)
Drought experience	0.0507**	0.0528**	0.0451*
	(0.0252)	(0.0247)	(0.0250)
Square of farm size	-0.000472***	-0.000477***	-0.000484***
	(0.000152)	(0.000151)	(0.000151)
Observations	408	408	408
R-squared	0.851	0.851	0.852

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' Compilation

In addition to weather variables, access to credit, education, experience, weather forecasting methods and farm size are significant drivers of technical efficiency of smallholder farmers in Hurungwe. Farmers with access to credit are 8% technically more efficient than farmers with no access to credit. In support of this finding, Hailu *et al*. (2014) and Uaiene *et al*. (2009) established that farmers with access to technology can afford better technologies that can improve their productivity. The statistical significance of a positive association between technical efficiency and education as buttressed by many previous studies (Masunda and Chiweshe, 2015; Ibrahim *et al*., 2014; Mapembe *et al*., 2013; Makki *et al*., 2012 and Singh *et al*., 2009) suggests that investment in education is critical for improving efficiency of smallholder farmers in rural Zimbabwe. A unit increase in the farmer's years of schooling increases technical efficiency of that farmer by 1.4% to 1.5%. The returns to formal education are however considered to be higher in areas with mechanised agricultural systems (Phillips, 1994). The results in model (3) further show that farmers who use modern weather forecasting methods are 4% more technically efficient than those using traditional methods although the coefficient is only statistically significant at 10% level. While experience can be regarded as the best teacher, in Hurungwe its impact on technical efficiency of farmers is very small despite its statistical significance. Technical efficiency increases by only 0.2% in every year increase in farming experience.

The question on whether small farms are efficiency enhancing has been addressed in this article. The findings in this article reveal a concave association between farm size and technical efficiency. The negative coefficient of the square of farm size suggests the existence of an optimal farm size which is 17 hectares obtained from maximizing model (3) with respect to farm size. With very small farm sizes, increases in farm size will increase technical efficiency but only up to 17 hectares, after which further increases in farm size will begin to negatively affect technical efficiency. There are diminishing returns in farm size. The quadratic association between technical efficiency and farm size may be the reason why previous studies established contradicting results. For example, Sherlund *et al*. (2002) and Sharma *et al*. (1999) established a positive association while Okon *et al*. (2010) and O'Neill *et al*. (2001) established the opposite. Many communal farmers in Hurungwe still require agricultural land while others have large tracks of land in excess of optimal land holdings which could be redistributed to improve technical efficiency of these farmers.

5. Conclusion and Policy Implications

This article first applied the stochastic frontier model to determine technical efficiency level of smallholder farmers in Hurungwe district. Second, the article made an attempt to model the determinants of technical efficiency with particular focus on the impact of drought on technical efficiency. With regards to technical efficiency levels, the results reveal that technical efficiency levels for smallholder farmers in Hurungwe are very low with an average of 45.3%. The findings show that drought is detrimental to technical efficiency of smallholder farmers. Farmers experiencing a drought shock are 19% less efficient than those experiencing wet weather conditions. However, knowledge and experience of droughts is an important driver of technical efficiency in the district. Furthermore, the results demonstrate that education, experience, access to credit and modern methods of weather forecasting contribute positively to technical efficiency while farm size has diminishing effects on technical efficiency. Gender, technology adoption and extension services are not associated with technical efficiency of Hurungwe farmers. The statistically significant findings have essential implications on policies aimed at improving technical efficiency of maize farmers in Zimbabwe.

First, the findings point to the need for the development of irrigation infrastructure in drought prone areas. Equally, the government can reduce the drought-induced technical efficiency losses by reallocating smallholder farmers to wet ecological areas of the district. The ongoing land reform will go a long way in improving technical efficiency of farmers in Hurungwe district if the government targets farmers in drought prone areas. The major policy implication of such findings is that if not checked, technical efficiency of maize farmers may worsen in the future due to climate change. Second, knowledge of drought history is important to the farmers as they prepare for the unforeseen. Farmers with drought experiences improve their efficiency levels. In this regard, the article recommends publication of drought information to farmers. This could be done by setting regional weather stations where farmers can freely obtain information with regards to weather and with regards to previous droughts. These local weather information centres can provide farmers with modern sources of weather forecasting.

Third, education is critical in the drive to improve technical efficiency of maize farmers. Programmes in education such as basic education assistance module (BEAM) should continue to receive support from the government and other developmental partners. Secondary education is a necessary condition for improving efficiency in agriculture especially in this era of mechanization. Fourth, access to credit increases farmers' technical efficiency. This finding points to an important policy implication that farmers can improve their quality of inputs hence productivity if they have access to credit. The result suggests that financial inclusion through establishment of rural banks and expansion of other rural financial services such as mobile banking is crucial for improving technical efficiency of maize farmers in Hurungwe.

Last, the impact of farm size on technical efficiency indicates that, on one hand, giving more land to farmers with farms less than 17 hectares will go a long way in increasing productive efficiency of maize farmers. The diminishing effects of farm size point to an important policy implication that when distributing land, the government should seriously consider the optimal land size. On the other hand, farmers with farms exceeding 17 hectares can have their excess land redistributed to those with smaller farms. The collected data however show that most farmers set aside a very small proportion of land for maize production while leaving the larger proportion for cash crops such as tobacco or leaving it fallow. It is in this view that this article recommends the government to carry out national campaigns which encourage farmers to expand maize hectrage. Future research should consider studying productive efficiency of maize farmers in other districts. Furthermore, future research should also look at optimal farm sizes and optimal other inputs such as fertilizer, labour and maize seed.

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