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Agricultural Management Practices and Factors Affecting Technical Efficiency in Zimbabwe Maize Farming

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Abstract: Integrating best management practices and improving the technical efficiency of smallholder maize farmers is critical in raising overall agricultural output. However, there is not much information, besides marginalization and high rehabilitation and maintenance costs, which adequately explains why productivity of smallholder irrigation farmers drop at very high rates. Therefore, this study measured technical efficiency, identified factors affecting technical efficiency, and identified best management practices adopted by smallholder maize irrigation farmers at Tokwane-Ngundu (Zimbabwe). The Data Envelopment Analysis, Double Bootstrap Approach in a Principal Component Regression was used. Primary data were gathered using a questionnaire. Empirical results revealed that the mean technical efficiency of the respondents was 77%, which indicated a potential for them to increase their efficiency by 30%. The factors that increased technical efficiency included human capital, extension contacts and compliance with best management practices. The policy implication of this study is the need for robust group incentive schemes to promote farmer-to-farmer skills transfer to boost the technical efficiency of smallholder maize irrigation farmers in Zimbabwe.

Keywords: management practice; technical efficiency; smallholder farmers; double bootstrap approach; principal component regression; human capital; gender

1. Introduction

Agriculture has been the mainstay of the Zimbabwean economy and Zimbabwe was regarded as the bread basket of the Southern Africa Development Community (SADC) region [1]. The overall importance of agriculture in Zimbabwe should be seen in the context of its role in promoting food security and foreign currency earning potential. Agriculture also promotes positive backward and forward multiplier linkages boosting employment creation, especially in the rural areas when farmers coordinate through cooperatives, contract farming and retail chains. Since independence, the government of Zimbabwe has strived to entrench a new integrated agricultural dispensation characterized by agrarian reforms where both large and small-scale farmers can compete on local and international commodity markets [2]. Within the wider ambit of agrarian reforms in Zimbabwe, small-scale irrigation schemes became prominent and were expected to remedy economic, social, and political relations.

Smallholder irrigation schemes in Southern Africa, instead of eradicating poverty, boosting food security, and promoting sustainable livelihoods, have often been criticized for their low agricultural productivity and negative environmental impact. Information as to why productivity of smallholder irrigation farmers drop at very high rates is lacking. This bothered Zimbabwean agricultural policy makers who expected smallholder irrigation farmers to use irrigation technology to boost

productivity [3]. Leared [4] further highlighted that the small-scale farming sector, far from being the 'engine of economic growth' in sub-Saharan Africa including Zimbabwe, has in fact become increasingly marginalised. This addresses the challenge of smallholder farmer development policies in Zimbabwe. Subsequently, the policies have to enable smallholder irrigation farmers to transcend subsistence farming to compete in local and international markets.

Zikhali [5] used the Cobb-Douglas production function to investigate the impact of the land reform programme on beneficiaries' agricultural productivity compared to a control group of communal farmers in Zimbabwe. The results suggested that land reform programme beneficiaries were more productive than communal farmers, largely due to differences in input usage such as fertilizer per hectare. Mushunje et al. [6] used the stochastic frontier function model of the Cobb-Douglas type to determine the technical efficiency of 44 cotton farmers from Mutanda resettlement scheme of Manicaland province in Zimbabwe. The technical inefficiency of cotton production decreased with increased family size and age of household head, but increased with farm size and education level of the household head. Mazvimavi et al. [7] analysed the productivity and efficiency of maize production under conservation agriculture and conventional farming in Zimbabwe by employing a stochastic production frontier model. The study indicated that even though conservation agriculture was practiced on smaller plots than conventional farming (0.36 ha compared to 0.85 ha respectively), it contributed about 50% to total maize production.

Most studies on technical efficiency use a stochastic frontier methodology [8–13]. Fewer studies, however, use a Data Envelopment Analysis (DEA). In this lesser-used approach, technical efficiency measurement follows a two-stage approach. The DEA efficiency scores are estimated in the first stage, followed by Tobit regression analysis in the second stage to explain inefficiencies, which become invalid since one of the main assumptions underlying regression analysis (no serial correlation) is violated [14,15]. To address the problem of serial correlation associated with the two-step DEA procedure, Simar and Wilson [15] propose an alternative estimation and statistical inference procedure based on a Double Bootstrap Approach (DBA). Kapelko [16] defines bootstrapping as a repeated simulation of the data-generating process (DGP) through resampling and applying the original estimator to each simulated sample so that resulting estimates imitate the original unknown sampling distribution of the estimators of interest. Jordaan [14] recommended the application of the double bootstrap approach of Simar and Wilson [15] within a Principal Component Regression (PCR) framework to eliminate any multicollinearity problem that may exist and distort the findings from the regression analysis.

Often, little research attention is paid towards compliance with best management practices as determinants of technical efficiency (see Table 1). Thus, there is little evidence of the scope for improving technical efficiency levels of smallholder farmers by focusing on compliance with best management practices rather than having to change the farm, personal and/or business characteristics of the farmer. Therefore, the objectives of this study were to measure the technical efficiency, identify factors affecting technical efficiency, and to identify best management practices adopted by smallholder maize irrigation farmers of Tokwane-Ngundu in Zimbabwe. The following research questions were addressed: To what level can farmers increase their efficiency? Which factors are most likely to impact on farmers' technical efficacy? What best management practices that farmers can adopt to enhance their efficiency? This study will be aiding decision makers in making efficient modifications to policies. The results will also contribute to increasing the sustainability of Zimbabwean smallholders (e.g., poverty alleviation and food security improvement) to comply with post-2015 agenda Sustainable Development Goals (2030-agenda) set by the United Nations. Even though this study was applied in Zimbabwe, the framework has the potential to be replicated in different case studies.

Table 1. Factors hypothesized to influence respondents' technical efficiency.

Variable	Measurement Index	Expected Sign
Human Capital		
Formal education	Highest level attained: 1 = None, 2 = Primary, 3 = Secondary or 4 = Tertiary	+
Farming experience	Number of years	+
Household size	Number of members per household	+
Farming qualification	Training received: 1 = Ordinary Farmer, 2 = Advanced Master Farmer, 3 = Tertiary and 4 = No training received	+
English proficiency	1 = Excellent, 2 = Good, 3 = Average, 4 = Below average and 5 = None	+
Arithmetic abilities	1 = Excellent, 2 = Good, 3 = Average, 4 = Below average, and 5 = None	+
Record keeping	Likert-type scale from 1–7	+
Extension Visits		
Frequency of extension visits	1 = Daily, 2 = Weekly, 3 = Per fortnight, 4 = Monthly, 5 = Quarterly and 6 = Never	+
Financial characteristics		
Access to off-farm income	1 = Yes, 2 = No	+
Lack of credit reduced farm productivity	1 = Strongly Agree, 2 = Agree, 3 = Undecided, 4 = Disagree and 5 = Strongly Disagree	-
Farming equipment		
Lack of farm equipment reduced farm productivity	1 = Strongly Agree, 2 = Agree, 3 = Undecided, 4 = Disagree and 5 = Strongly Disagree	-
Compliance with best management practices (Likert-type scale from 1–7 (1 = not at all, 7 = completely))		
Ploughing depth		+
Land disking		+
Land harrowing		+
Intra-row spacing		+
Inter-row spacing		+
Timely irrigating		+
Sufficient irrigating		+
Weed control		+
Crop rotation		+
Preventing soil erosion		+
Preventing soil compaction		+
Preventing nutrient leaching		+
Pest control		+
Disease control		+

Tokwane-Ngundu Smallholder Irrigation Scheme

Tokwane-Ngundu smallholder irrigation scheme is found in Chisase village, Masvingo District, which is in the dry and semi-arid part of Zimbabwe. The village was formed in 1988 under the government's land resettlement programme and transformed into an irrigation scheme in 2002. The scheme shares its boundaries with the Mwenezi Ranch to the south and the Nuanetsi Ranch to the east while the Neshuro and Magudu communal lands are to the scheme's east and west, respectively. The irrigation scheme is located 40 km away from Triangle and Hippo Valley Sugar Estates and 60 km away from the town of Chiredzi [17].

The irrigation scheme is located along the Chiredzi-Masvingo highway and draws its water from the Tokwane dam, which is approximately 8 km to the south. The water canal that takes water from the Tokwane Dam to the Triangle Sugar estates pass through the irrigation scheme and the villagers have reliable access to water for domestic use. There is an electrical power line that passes through the irrigation scheme, which the farmers cannot access.

The community members felt that an irrigation scheme had the potential to transform their agricultural endeavours and reduce the level of poverty in their village. The majority of the villagers reckoned that the Tokwane Dam and canal's water resources could be harnessed to irrigate their crops throughout the year. The villagers also pointed to success stories of other smallholder irrigation schemes at Mushandike and Magudu and they argued that the irrigation scheme would transform their livelihoods for the better [18].

Sixty households that comprised the Chisase village were subsequently allocated plots into what came to be Tokwane-Ngundu Smallholder Irrigation Scheme. Each household was allocated four hectares of arable land for irrigation purposes. The irrigation scheme was divided into four blocks (blocks A to D). Each block has approximately fifteen irrigation plots. The irrigation scheme was designed to use the furrow irrigation method and water flows in the furrows due to natural slope and gradient differences. The water is channelled from the main irrigation scheme into the fields through a series of smaller concrete feeder canals. Each block also has a borehole that is supposed to provide clean and safe water for human consumption and domestic use. There is a Blair toilet for every five plots in each block.

2. Materials and Methods

2.1. Study Area

The study area (Figure 1) is located in Masvingo province, Zimbabwe that comprises seven administrative districts (Gutu, Masvingo, Bikita, Chivi, Zaka, Mwenezi, and Chiredzi). Masvingo province is located in the low-veld of the country where rainfall is minimal and uncertain. Most of the southern part of the province is drought prone. Most parts of the province depend on irrigation [19].

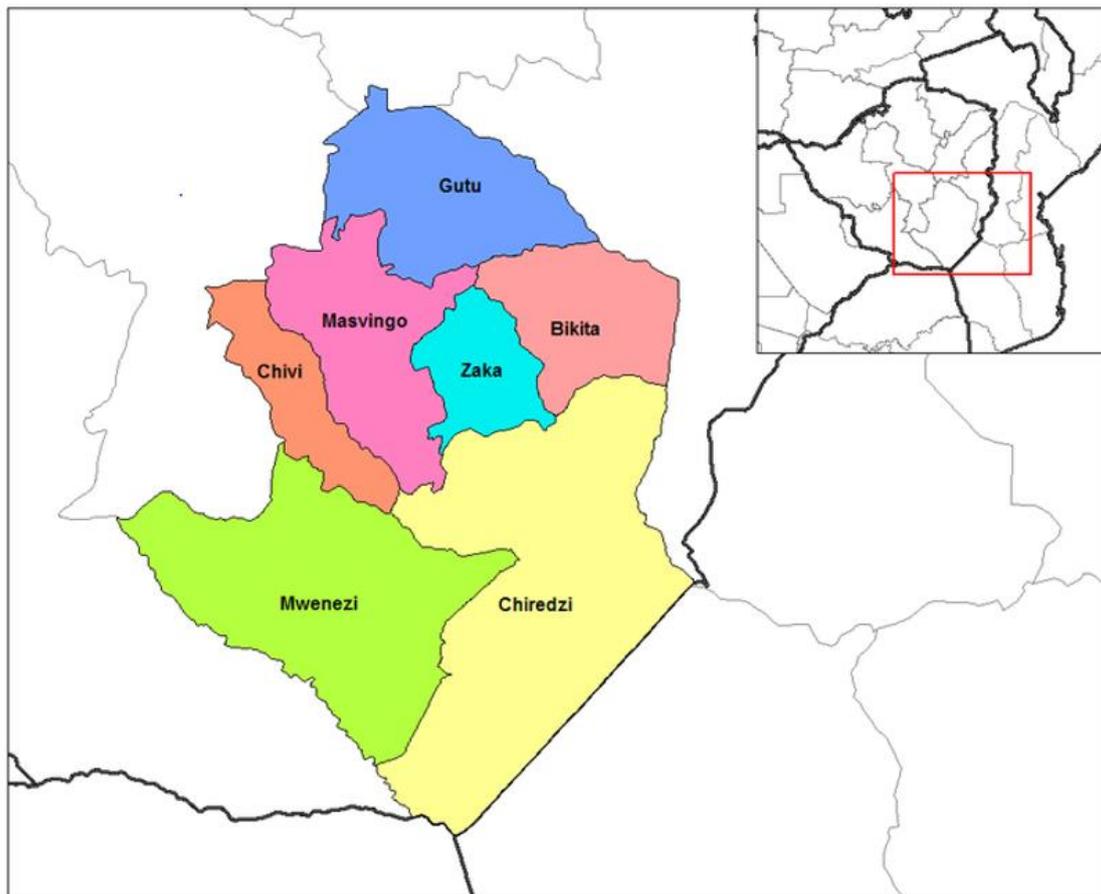


Figure 1. Masvingo Province of Zimbabwe. Source: Sabastain [17].

2.2. Sampling Procedure and Data

The Tokwane-Ngundu Smallholder Irrigation Scheme was selected using non-probability convenience sampling due to its proximity to the Researchers. Simple random sampling was used to sample plot holders from a pool of 60 to participate in focus group discussions. The other 50 plot holders answered a semi-structured questionnaire. Information on the 2011 maize production season was collected from July to October 2012 using the semi-structured questionnaire. The questionnaires of [14,20,21] were adapted and served as a guide for this study. Questions included socioeconomic characteristics and determinants of technical efficiency (human capital, financial aspects, extension services and compliance with best management practice), as explained in Tables 1–3. The questionnaire was constructed to measure technical efficiency levels and investigate the determinants of farmers' technical efficiency. The study also set out to collect data relating to the inputs used by the farmers to achieve their maize output per hectare.

The input and output data were necessary for the calculation of farmers' technical efficiencies and to determine the factors that affected their technical efficiency. The input data included the amount of fertilizer (nitrogen, phosphorus and potassium) applied per hectare, and amount of labour (both family and hired labour) in man-days per hectare. These variables served as a basis for physical inputs used for producing maize per production season in the study area. The collected data was analysed using R software.

Table 2. Socioeconomic characteristics of respondents.

Characteristics							Total
Gender	Male	Female					
Frequency	33	17					50
Age	<20	20–35	36–55	>56			
Frequency	0	16	21	13			50
Household size	4–6	7–9	10–12	13–15	>15		
Frequency	23	18	6	2	1		50
Educational level	None	Primary	Secondary	Tertiary			
Frequency	8	14	25	3			50
Farming qualification	None	OFT *	AMFT **	Diploma			
Frequency	44	4	1	1			50
Extension service access	Weekly	Two weekly	Monthly	Quarterly	Never		
Frequency	7	13	20	3	7		50
Extension service quality	Poor	Average	Good	Excellent			
Frequency	15	17	16	2			50
Off-farm income	Formal employment	Remittances	Informal trading	Formal trading			
Frequency	3	10	6	1			20

Note: OFT * ordinary farmer training and AMFT ** advanced master farmer training.

Table 3. Regression results from the truncated bias-corrected technical efficiency scores.

Human Capital	Coefficient	Standard Error	Z-Statistic	Prob (z)
Arithmetic abilities	−2.55	0.041	−62.88	0.000 ***
English proficiency	−2.49	0.041	−61.16	0.000 ***
Household size	−2.17	0.038	−57.27	0.000 ***
Formal education	−0.46	0.035	−13.14	0.000 ***
Farming experience	−0.43	0.039	−11.00	0.000 ***
Farm qualification	0.81	0.039	20.58	0.000 ***
Extension Visits				
Extension frequency	−0.82 *	0.04	−19.04	0.000 ***
Financial Aspects				
Off-farm income	2.55	0.03	77.26	0.000 ***
Access to credit	0.38	0.05	8.11	0.000 ***
Farming Equipment				
Farming equipment	0.49 *	0.04	11.21	0.000 ***
Compliance with Best Management Practices				
Weed control	−1.26	0.044	−28.52	0.000 ***
Disease control	−1.04	0.049	−21.21	0.000 ***
Crop rotation	−0.89	0.043	−20.46	0.000 ***
Ploughing depth	−0.89	0.043	−20.71	0.000 ***
Pest control	−0.692	0.046	−15.14	0.000 ***
Harrowing	−0.58	0.037	−15.75	0.000 ***
Land disking	−0.41	0.035	−11.89	0.000 ***
Intra-row spacing	−0.40	0.058	−6.85	0.000 ***
Inter-row spacing	−0.29	0.058	−4.99	0.000 ***
Sufficient irrigation	−0.09	0.035	−2.63	0.015 **
Preventing soil erosion	−0.01	0.042	−0.26	0.796
Timely irrigation	0.28 ***	0.041	6.76	0
Preventing soil compaction	0.43	0.045	9.46	0.000 ***
Record keeping	1.14	0.043	26.57	0.000 ***
Preventing leaching	2.15	0.031	69.11	0.000 ***

Note: ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

2.3. Conceptual Framework of Data Envelopment Analysis (DEA), Double Bootstrap Approach (DBA), within a Principal Component Regression (PCR)

This study follows DEA DBA within a PCR framework to estimate and explain technical efficiency levels of the sample of maize producers. More specifically, this study uses the DEA double bootstrap approach of Simar and Wilson [22] to estimate and explain technical efficiency or productivity differentials. This technique overcomes severe limitations inherent in using the two-stage DEA approach commonly employed in efficiency literature [23]. The procedure employed in this research is referred to as Algorithm 2 by Simar and Wilson [22]. The regression analysis within Algorithm 2 of Simar and Wilson [22], is performed within the PCR framework to reduce the number of explanatory variables relative to the number of observations [14]. A detailed discussion of the mathematical model is presented in Appendix A.

2.4. Factors Hypothesized to Influence Technical Efficiency Levels of the Respondents

The factors hypothesized to influence the level of technical efficiency of respondents are shown in Table 1. Table 1 shows that technical efficiency levels were hypothesised to be positively affected by human capital Wouterse [24]; Maseatile [21], extension visits Belcombe et al. [25], access to off-farm income and credit Maseatile [21], Belcombe et al. [25], and compliance with best management practices [14,20]. The lack of access to farming equipment were hypothesised to contribute to technical inefficiency of the respondents [24].

3. Results and Discussion

3.1. Socioeconomic Characteristics of Respondents

Table 2 summarises the respondents' socioeconomic characteristics at Tokwane-Ngundu smallholder irrigation scheme. Three-quarters (66%) of the respondents were men. The ratio of men to women in terms of plot occupancy was therefore almost 2:1. Participation of women in agriculture remains a challenge among maize farmers in Zimbabwe, because of the gender stereotype that farming is a masculine preserve. The majority (68%) of the respondents were above 35 years old. During the interviews, respondents highlighted a concern that farming did not attract enough young entrants.

Most respondents (84%) had at least a primary education. This finding is consistent with Zimbabwe's overall rating as one of the most literate countries in Africa [26]. Farming experience did not show great variation as most of the respondents reported eight years' experience in irrigation farming. The irrigation scheme was set up in 2002 and the plots were subsequently allocated at the same time. Consistent with small-scale farming in developing countries, respondents' land sizes were generally small (4 hectares on average). Only one plot holder had double (8 ha) the average plot size.

The household sizes were relatively large, with 54% having at least seven members, and 3 households with 13 members or more. A consensus among respondents is that the larger the household size, the more labour will be available for irrigation maize farming activities. The average household size is consistent with the average family size in African tradition of a large family, comprising about eight people, to provide farm labour during peak production periods.

In terms of extension service access, 84% of the respondents had been visited by an extension officer at least once in a quarter. Extension service access was therefore generally high. However, a cause for concern is that 16% of the respondents reported no extension service access at all even though there was an extension officer exclusively earmarked for the irrigation scheme. Some of the respondents reported that the extension officer showed favouritism in his official execution of duties. Another worrisome issue is that the majority (64%) of the respondents reported the quality of extension service to be either average or poor. This might mean that the respondents are not advised to the required standard with negative implications for their performance and productivity.

Only twenty (40%) of the respondents had access to off-farm income. The findings show that the livelihood strategies of the respondents were generally limited to farming with minimal diversification. In case of crop failure, the respondents' livelihoods could come under threat. Off-farm income can be used to buy or access agro-inputs in order to boost respondents' performance.

3.2. Technical Efficiency Levels of Respondents

The bias-corrected technical efficiency scores of respondents are shown as a cumulative probability distribution in Figure 2. Figure 2 shows that the estimated technical efficiencies for the respondents ranged from 29% to 100%. The mean technical efficiency of the respondents was 77%. Thus, there is a potential for respondents to increase their efficiency by 23% if they use existing farm resources efficiently. Figure 2 also shows that about 48% of the respondents had technical efficiency scores of one. This indicated that they produced their maize on the efficiency frontier and were deemed technically efficient. The remainder of the respondents (52%) had technical efficiency scores below one and therefore were technically inefficient. The technically inefficient respondents have the potential to increase their maize output at a given level of input within the existing technology set. Moreover, Figure 2 also indicated that 50% of the respondents achieved technical efficiency scores lower than 0.8. Thus, 50% of the respondents produced less than 80% of the yields that they should have been able to produce at current input levels. The least technically efficient respondent (0.29) should be able to increase his or her current output by $244\% = (1/0.29 - 1) \times 100$ at current input levels, and within the existing technology set.

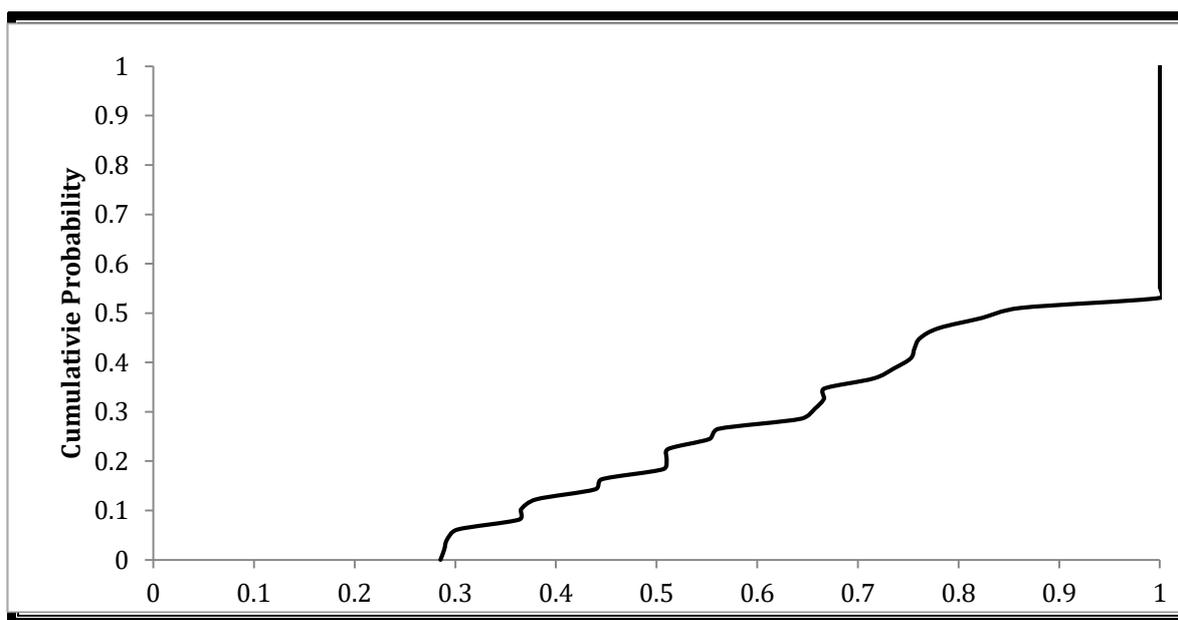


Figure 2. Cumulative probability distribution of technical efficiency scores.

3.3. Determinants of Technical Efficiency

Table 3 shows results from the regression analysis of the bias-corrected technical inefficiency scores on the factors that were hypothesized to influence the technical efficiency levels of the respondents. With respect to human capital, five of the variables significantly increased the technical efficiency of the respondents. The negative signs on formal education, farming experience, household size, English proficiency, and arithmetic abilities imply that higher levels of these characteristics are associated with higher technical efficiency levels of the respondents. The findings confirm the initial hypothesis and are in agreement with the results of [14,20,24,27,28]. However, contrary to the initial hypothesis, possession of a farming qualification was negatively related to the technical efficiency of respondents.

This proves that the mere possession of a qualification in farming does not guarantee that the technical efficiency of the qualification holder will be increased.

The frequency of extension officers' visits was positively associated with respondents' technical efficiency, thus the initial expectation was confirmed. This finding is consistent with that of Belcombe et al. [25] and Haile [29], who showed that training had positive effects on efficiency levels. Training provides knowledge, skills and insights that can improve farmers' overall efficiency and productivity.

Both of the hypotheses surrounding financial characteristics of respondents were rejected in this study. Off-farm income and access to credit significantly reduced the technical efficiency of the respondents. This was in opposition to Jordaan [14] and Maseatile, [21], but in agreement with those of Haile [29]. The credit access results can be explained that in case the credit is not accessed on time, it may, more often than not, lead to misapplication of funds. Hence, the expected impact of such funds will not be felt on the farm [29]. The negative impact of off-farm income on technical efficiency was also noted by [25,28]. This could be because off-farm income tends to be mainly from wage earnings, which implies less time is allocated for farm work with a negative impact on technical efficiency [25].

It was hypothesized that farming equipment would increase the respondents' technical efficiency. However, this initial expectation was not proved and ownership of farm equipment actually reduced technical efficiency of the respondents. This shows that owning farm equipment is not in itself a sufficient condition to achieve high technical efficiency levels. For instance, owning implements without the requisite labour will not translate to higher technical efficiency. These findings are particularly interesting in the Zimbabwean context where government and the central bank have advocated and spearheaded an aggressive farm credit and farm mechanisation programme.

As expected, 11 out of 14 of the best management practices in maize irrigation farming were significant and positively correlated with the respondents' technical efficiency. The results showed that respondents who complied with recommended ploughing depth, disk their fields after ploughing, harrow their fields, observe both intra-row and inter-row spacing, irrigate their crops sufficiently, weed their crops regularly, practice regular crop rotation, and protect their crops from pests and disease, are more technically efficient than their counterparts who do not observe the best management practices. However, timely irrigation, preventing soil compaction, and preventing nutrient leaching increased the respondents' technical inefficiencies, hence the initial hypotheses were not confirmed.

The prevention of soil erosion was insignificant in explaining respondent's technical efficiency. Thus, one cannot make a distinction of the respondents' technical efficiency based on their actions to prevent soil erosion. The coefficient of leaching prevention was positive, hence the variable increased respondents' technical inefficiencies. Preventing nutrient leaching was expected to maintain and preserve soil fertility and quality in general and improve respondents' technical efficiency. The prevention of soil compaction was expected to preserve soil structure for easier root penetration and water percolation, aiding proper growth and development of maize crops.

The findings confirm that irrigating maize crops on time needed to be complemented with sufficient amounts of water application to avoid moisture stress. Khaile [20] noted that record keeping is important in farming activities, as it is an important management tool showing attention to detail. However, in this study, record keeping was associated with lower levels of technical efficiency of the respondents.

4. Conclusions

The aim of this paper was to measure technical efficiency, identify factors affecting technical efficiency, and to identify best management practices adopted by smallholder maize irrigation farmers at Tokwane-Ngundu in Zimbabwe. Results showed that the respondents' mean technical efficiency was 77% and it indicated that there is a potential for them to increase their efficiency by 30%. Further, the results confirm human capital, compliance with best management practices, and participatory extension service were significant and associated with enhancing technical efficiency. However, financial characteristics (lack of access to credit and lack of off-farm income) and owning farm equipment were

associated with decrease of production and respondents’ technical efficiencies. The study concludes that it is not necessary to change personal, farm, or financial characteristics of smallholder farmers to improve their technical efficiency.

By merely helping farmers with the basics to comply with best management practices, significant gains are possible. Moreover, helping farmers to comply with best management practices may be cheaper and easier than changing the characteristics of the farmers. Such changes may then contribute towards increasing the efficiency levels of the farmers. Policy makers in maize irrigation farming have to improve the farmers’ motivation and attitudes to comply with best management practices in order to boost productivity. Robust agricultural extension services are needed to expedite building human capital among the farmers. Relevant and up to date extension services are especially necessary to ensure that farmers follow the recommended best management practices. Thus, it is recommended that more emphasis be placed on back-to-basics training by extension officers. Policies that facilitate more effective extension services and education among the smallholder farmers by involving especially women and younger people.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

The procedure is summarised in the following seven steps:

Step 1: Estimate output-oriented data envelopment analysis efficiency scores “ $\hat{\delta}_i$ ”. The analysis approach is performed as follows:

$max \hat{\delta}_i$ subject to:

$$x_{ij0} \geq \sum_{j=1}^n x_{ij} \lambda_j \quad (i = 1, \dots, I) \tag{A1}$$

$$\delta_i y_{pj0} \leq \sum_{j=1}^n y_{pj} \lambda_j \quad (P = 1, \dots, P) \tag{A2}$$

$$\sum_{j=1}^n \lambda_j \leq 1 \quad (j = 1, \dots, J) \tag{A3}$$

$$\lambda_j > 0;$$

where ‘ x_{ij} ’ defines the amount of input ‘ i ’ used by decision-making unit (smallholder maize irrigation farmers) ‘ j ’. ‘ y_{pj} ’ is the amount of product ‘ p ’ produced by decision-making unit (smallholder maize irrigation farmers), hence the outcome variable is maize produced in ton per hectare during the 2011 production season as indicated by ‘ y_{pj} ’, ‘ j ’ and ‘ j_0 ’ refers to the reference decision-making unit (smallholder maize irrigation farmers) for which the efficiency is calculated. ‘ λ_j ’ indicates the non-negative weights that are optimized for each decision-making unit. The weights measure the location of an inefficient decision-making unit (smallholder maize irrigation farmers) if it was to become technically efficient. The restriction, ‘ $\sum_{j=1}^n \lambda_j \leq 1$ ’, specifies variable returns to scale. ‘ δ_i ’ is greater or equal to one and represents the efficiency score that measures the technical efficiency of the ‘ i th’ decision-making unit (smallholder maize irrigation farmers) as the distance to the efficiency frontier. The efficiency frontier is a linear combination of best practice observations. Decision-making units

with ' $\delta_i = 1$ ' are on the efficiency frontier and are considered to be technically efficient decision-making units with ' $\delta_i > 1$ ' inside the efficiency frontier and considered to be inefficient.

The production inputs that were used to estimate the data envelopment analysis technical efficiency scores ' X_{ij} ' include the amount of Nitrogen (N), Phosphorus (P), Potassium (K), and labour. The N, P, and K were measured as the amount (in kilograms) that was applied per hectare. Labour was measured as the number of labour days that were used per hectare.

Step 2: The maximum likelihood method is used to obtain an estimate ' $\hat{\beta}$ ' of ' β ' and an estimate ' σ_ε ' of ' σ_ε ' from the truncated regression of the estimated efficiency scores ' δ_i ' on explanatory variables ' z_i ' using the observations when ' $\delta_i > 1$ '.

The explanatory variables ' z_i ' are principal components that were extracted, by means of a PCA, on all of the variables that were originally hypothesized to influence the technical efficiency levels of respondents (summarised in Table A1). The procedure to extract the principal components starts with the standardization of the hypothesized explanatory variables. All of the standardized variables have averages of zero and standard deviations of one. The standardized explanatory variables are used in a principal component analysis to calculate eigenvectors, which are used to construct the principal components. Following the Kaiser-Gutman rule, only principal components with eigenvalues greater than one are included in the regression analysis. Table A1 shows the eigenvalues of the principal components of the variables that were initially hypothesized to influence the technical efficiency of respondents.

Table A1. Summary of eigenvalues of principal components.

Principal Component	Eigenvalue	Individual %	Cumulative %
1	4.31	17.26	17.26
2	3.24	12.97	30.23
3	4.01	16.03	46.25
4	1.49	5.98	52.23
5	1.52	6.08	58.30
6	2.28	9.11	67.42
7	1.95	7.79	75.20
8	0.86	3.45	78.65
9	0.78	3.11	81.76
10	0.73	2.92	84.68
11	0.67	2.69	87.37
12	0.53	2.11	89.48
13	0.51	2.05	91.53
14	0.38	1.53	93.06
15	0.33	1.33	94.38
16	0.30	1.20	95.58
17	0.25	1.00	96.58
18	0.21	0.86	97.44
19	0.16	0.64	98.09
20	0.15	0.59	98.68
21	0.13	0.50	99.18
22	0.08	0.34	99.52
23	0.07	0.27	99.79
24	0.04	0.14	99.93
25	0.02	0.07	100

Table A1 shows that seven of the 25 principal components have eigenvalues greater than one. Cumulatively the seven principal components explain 75% of the variation in the explanatory variables, which are included in the principal components. Based on the eigenvalues in Table 1, seven principal components are included in the truncated regression analysis in Step 2 to obtain estimates ' $\hat{\beta}$ ' of ' β ' and ' σ_ε ' of ' σ_ε '.

Step 3: Loop over the next four steps (3.1)–(3.4) L_1 times to obtain n sets of bootstrap estimates $(\delta_{ib}^*)_{b=1}^{L_1}$:

- 3.1. For each $i = 1 \dots, n$, draw ε_i' from the $N(0, \hat{\sigma}_\varepsilon^2)$ distribution with left truncation at $(1 - z_i \hat{\beta})'$.
- 3.2. Again for each $i = 1 \dots n$, compute $\delta_i^* = Z_i \hat{\beta} + \varepsilon_i'$
- 3.3. Set $x_i^* = x_i'$ and $X_i^* = y_i \delta_i / \delta_i^*$ for all $i = 1, \dots$.
- 3.4. Compute δ_1^* using the bootstrap samples of X_i^* and y_i^* from step (3.3).

Simar and Wilson [22] pointed out that 100 bootstrap replications tend to be sufficient to estimate the bias-corrected technical efficiency scores $\tilde{\delta}'$ in Step 4. L_1 in Step 3 is thus set to 100.

Step 4: Compute the bias-corrected efficiency scores $\tilde{\delta}'$ for each $i = 1, \dots, n$ using the bootstrap estimates in step (3.4) and the original estimate $\hat{\delta}'$. The bias-corrected efficiency score is calculated as follows: $\tilde{\delta} = \hat{\delta} - \text{bias}_i$. Where bias_i is the bootstrap estimator of bias obtained by the formula (14):

$$\text{bias}_i = \left(\frac{1}{L_1} \sum_{b=1}^{L_1} \delta_{ib}^* \right) - \hat{\delta}_i \tag{A4}$$

Step 5: Use the maximum likelihood method to estimate the truncated regression of $\tilde{\delta}'$ on z_i' to obtain estimates $(\tilde{\beta}, \tilde{\sigma})'$. Again the principal components of the explanatory variables are used as z_i' in the truncated regression.

Step 6: Loop over the next three steps (6.1)–(6.3) L_2 times to obtain a set of bootstrap estimates $\{(\hat{\beta}_b^*, \hat{\sigma}_b^*)_{b=1, \dots, L_2}\}$

- 6.1. For each $i = 1 \dots, n$, draw ε_i' from the $N(0, \tilde{\sigma})$ distribution with left truncation at $(1 - z_i \tilde{\beta})'$
- 6.2. Again for each $i = 1 \dots, n$, compute $\delta_i^{**} = z_i \tilde{\beta} + \varepsilon_i'$
- 6.3. Use maximum likelihood method to estimate the truncated regression of δ_i^{**} on z_i' to obtain $(\tilde{\beta}^*, \tilde{\sigma}^*)'$ (The principal components of the explanatory variables are used as z_i' in the truncated regression of δ_i^{**} on z_i' to obtain $(\tilde{\beta}^*, \tilde{\sigma}^*)'$

Simar and Wilson [22] set L_2 to 2000 bootstrap replications. A larger number of replications are more likely to yield more accurate results. The results from the truncated regression of the bias-corrected technical inefficiency scores on the seven principal components with eigenvalues greater than one are shown in Table A2.

Table A2. Truncated regression results.

Variable	Coefficient	Standard Error	Z-Statistic	Prob (z)
Intercept	47.81	0.10	479.12	0.000 ***
ZPC1	0.45	0.15	3.11	0.003 **
ZPC2	5.34	0.07	79.73	0.000 ***
ZPC3	-1.21	0.11	-11.15	0.000 ***
ZPC4	2.73	0.07	37.6	0.000 ***
ZPC5	0.04	0.05	0.80	0.427
ZPC6	0.02	0.06	0.26	0.794
ZPC7	0.13	0.05	2.77	0.008 *

Note: ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Table A2 shows that all the variables except two are significant. This shows that six of the principal components are significant in explaining the variation in the bias-corrected technical efficiency scores of respondents. Following the procedures by Jordaan [14] and Khaile [20], the coefficients $(\tilde{\beta}^*)'$ and standard errors $(\tilde{\sigma}^*)'$ from the truncated regression analysis are used to calculate the coefficients of the individual standardized variables that were included in the principal components and the standard errors of the coefficients of the standardized variables.

The coefficients of the standardized variables are divided by the standard deviations of the original explanatory variables in order to get un-standardized coefficients. In a similar manner, un-standardized standard errors are also obtained by dividing the standard errors of the standardized coefficients by the standard deviations of the original explanatory variables. The un-standardized coefficients and standard errors are then used to calculate z-values and the probabilities of the z-values to determine the levels of significance of the respective un-standardized explanatory variables as determinants of technical efficiency.

Step 7: Use the bootstrap values ($\tilde{\beta}^*$, $\tilde{\sigma}^*$) to construct $(1 - \alpha)$ confidence intervals for each element of β and $\hat{\sigma}_\varepsilon$ as follows:

$$\text{Prob}(\text{Lower}_{\alpha,j} \leq \beta_j \leq \text{Upper}_{\alpha,j}) = 1 - \alpha \quad (\text{A5})$$

where $\text{Lower}_{\alpha,j}$ and $\text{Upper}_{\alpha,j}$ are calculated using the empirical intervals obtained from the bootstrap values $\text{Prob}(-b_\alpha \leq \hat{\beta}_j^* - \hat{\beta}_j \leq -\hat{a}_\alpha) \approx 1 - \alpha$ and $\text{Upper}_{\alpha,j} = \hat{\beta}_j + \hat{b}_\alpha$; $\text{Lower}_\alpha = \hat{\beta}_j + \hat{a}_\alpha$.

References

1. Ntsebeza, L. The Land Question in Southern Africa: A comparative view. In *The Land Question in South Africa: The Challenges of Transformation and Redistribution*; Ntsebeza, L., Hall, R., Eds.; Human Sciences Research Council (HSRC): Pretoria, South Africa, 2007.
2. Musemwa, L.; Mushunje, A. Factor affecting yield crops and land utilization amongst land reform beneficiaries of Mashonaland central province in Zimbabwe. *J. Dev. Agric. Econ.* **2012**, *4*, 109–118. [[CrossRef](#)]
3. Veldswisch, G.J.; Bolding, A.; Wester, P. Sand in the Engine: The travails of an irrigated rice scheme in Bwanje Valley, Malawi. *J. Dev. Stud.* **2009**, *2*, 197–226. [[CrossRef](#)]
4. Leared, H. *The Case for Agricultural Hubs as Platforms for Growth and Development in sub-Saharan Africa*; Perspectives on Agriculture: Discussion Paper 2010/06; Brenthurst Foundation Ltd.: Johannesburg, South Africa, 2010.
5. Zikhali, P. *Fast Track Land Reform and Agricultural Productivity in Zimbabwe*; Discussion Paper Series, No.08-30; Environmental Policy Research Unit (EPRU); University of Cape Town: Cape Town, South Africa, 2008.
6. Mushunje, A.; Belete, A.; Fraser, G. Technical Efficiency of Resettlement Farmers of Zimbabwe. Presented at the 41st Annual Conference of the Agricultural Economics Association of South Africa, Pretoria, South Africa, 2–3 October 2003.
7. Mazvimavi, K.; Ndlovu, P.V.; Henry, A.; Murendo, C. Productivity and Efficiency Analysis of Maize under Conservation Agriculture in Zimbabwe. Presented at the International Association of Agricultural Economists Triennial Conference, Foz do Iguacu, Brazil, 18–24 August 2012.
8. Binam, J.N.; Tonye, J.; Wandji, N. Source of technical efficiency among small holder maize and peanut farmers in the Slash and Burn agricultural zone of Cameroon. *J. Econ. Coop.* **2005**, *26*, 193–210.
9. Coelli, T.; Battese, G.E. Identification of factors which influence the technical inefficiency of Indian farmers. *Aust. J. Agric. Econ.* **1996**, *40*, 103–128. [[CrossRef](#)]
10. Mkhabela, T. Technical efficiency in a vegetable based mixed-cropping sector in Tugela Ferry Msinga district, Kwazulu-Natal. *Agrekon* **2005**, *44*, 187–204. [[CrossRef](#)]
11. Mor, S.; Sharma, S. Technical efficiency and supply chain practices in dairying: The case of India. *Agric. Econ.* **2012**, *58*, 85–91. [[CrossRef](#)]
12. Nkegbe, P.K. Technical efficiency in crop production and environmental resource management practices in northern Ghana. *Environ. Econ.* **2012**, *3*, 43–51.
13. Tesfay, W.; Beshir, H. Determinants of technical efficiency in maize production: The case of smallholder farmers in Dhidhessa District of Illuababora Zone, Ethiopia. *J. Econ. Sustain. Dev.* **2014**, *5*, 274–285.
14. Jordaan, H. *New Institutional Economic Analysis of Emerging Irrigation Farmers' Food Value Chains*. Ph.D. Thesis, University of the Free State, Bloemfontein, South Africa, 2012.
15. Simar, L.; Wilson, P.W. A general methodology for bootstrapping in non-parametric frontier models. *J. Appl. Stat.* **2000**, *27*, 779–802. [[CrossRef](#)]

16. Kapelko, M. Application of DEA Model with Bootstrap to Evaluation of SMEs Efficiency in the Spanish Textile Industry. In *Multiple Criteria Decision Making 10–11*; Trzaskalik, T., Wachowicz, T., Eds.; University of Economics in Katowice: Katowice, Poland, 2010; pp. 133–148.
17. Sabastain, G. The Productivity of Smallholder Maize Farmers at Tokwane-Ngundu Irrigation Scheme in Masvingo District, Zimbabwe. Ph.D. Thesis, University of the Free State, Bloemfontein, South Africa, 2013.
18. Jongwe, J. In Proceedings of the Personal Interview—District Development Officer, Masvingo District, Zimbabwe, 4 January 2012.
19. Mupedziswa, R. *Policy Making Issues in Southern Africa*; SAPES: Harare, Zimbabwe, 2003.
20. Khaile, P.M.E. Factors Affecting the Technical Efficiency of Small-Scale Raisin Producers in Eksteenskuil. Ph.D. Thesis, University of the Free State, Bloemfontein, South Africa, 2012.
21. Maseatile, M.S.M. Productivity of Small Scale-Farmers in Zimbabwe. Ph.D. Thesis, University of the Free State, Bloemfontein, South Africa, 2011.
22. Simar, L.; Wilson, P.W. Estimation and inference in two-stage semi-parametric models of production processes. *J. Econ.* **2007**, *136*, 31–64. [[CrossRef](#)]
23. Baten, A.; Hossain, I. Stochastic frontier model with distributional assumptions for Rice production technical efficiency. *J. Agric. Sci. Technol.* **2014**, *16*, 481–496.
24. Wouterse, F. *Social Services, Human Capital and Technical Efficiency of Smallholders in Burkina Faso*; Discussion Paper 01068; International Food Policy Research Institute (IFPRI): Washington, DC, USA, 2011.
25. Belcombe, K.; Fraser, I.; Latruffe, L.; Rahman, M.; Smith, L. An application of the DEA Double Bootstrap to examine sources of efficiency in Bangladesh rice farming. *Appl. Econ.* **2008**, *40*, 1919–1925. [[CrossRef](#)]
26. The African Economist. Ranking of African Countries by Literacy Rate: Zimbabwe No.1. 2013. Available online: <http://www.theafricaneconomist.com> (accessed on 4 October 2019).
27. Basnayake, B.; Gunaratne, B. Estimation of technical efficiency and its determinants in the tea small holding sector in the mid country wet zone of Sri Lanka. *Sri Lank. J. Agric. Econ.* **2002**, *4*, 137–150. [[CrossRef](#)]
28. Obwona, M. *Determinants of Technical Efficiency Differentials among Small- and Medium-Scale Farmers in Uganda: A Case of Tobacco Growers*; Research Report 152; African Economic Research Consortium: Nairobi, Kenya, 2006.
29. Haile, B.T. Determinants of Technical, Allocative and Economic Efficiencies among onion producing farmers in irrigated agriculture: Empirical evidence from Kobo district, Amhara region, Ethiopia. *Afr. J. Agric. Res.* **2015**, *10*, 2180–2189.



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