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Technical Efficiency of Tilapia Production in Malawi And China: Application of Stochastic Frontier Production Approach

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Abstract

In the present study, stochastic frontier production function was applied to estimate both the technical efficiency scores and determinants of inefficiency for 20 tilapia farms apiece in Malawi and China. The study used the Cobb-Douglas model in which efficiency estimates showed that tilapia farmers in Malawi were more technically inefficient than farmers in China, with mean efficiency scores of 47% and 91% respectively. With exception of aquaculture experience, all the inefficiency determinants were positive for Malawian farms even though none of the coefficients was significant. For Chinese tilapia farmers, age (significant), household size and education had negative signs except aquaculture experience. The Malawian tilapia industry need technology innovations in order to reduce the existing 53% yield gap, which can ideally be introduction or development of new strains of superior quality, enhanced use of all-male tilapia, improvement in both nursing and grow-out technologies as well as use of quality fish feed.

Keywords: Stochastic frontier production; Technical efficiency; Tilapia; Elasticity; Cobb Douglas

Introduction

Background information

Global fish production from both the capture fisheries and aquaculture is not keeping pace with its growing demand from a growing population, and Malawi and China are no exceptions. Malawi's annual per capita fish consumption was 8.12 kg in 2014 [1], which is short of the global and China's per capita of 19.7 kg and 37.9 kg respectively [2]. This is clear indication that there is great shortage of fish production in Malawi. With human consumption of farmed species exceeding that of capture fisheries for the first time in 2014, FAO [2] reports that aquaculture is expected to further increase its share and provide 57 percent of fish for human consumption in 2025. Increased aquaculture production can help to meet the increased domestic demand for fish and also to meet protein availability. However, between 2010 and 2014, annual aquaculture production in Malawi has slowly increased from 2346 to 4119.48 metric tons [3]. This slow growth is attributed to a number of factors including poor quality fingerlings from a genetically depreciated strain, poor quality feed, and use of archaic technologies in the production system. These high-risk challenges have resulted in high fish mortality and low growth, which, adversely affected yield as well as production cost. Use of archaic technologies have brought technical inefficiency which has a great effect in productivity of aquaculture establishments. Thus, focussing on a mere increase in number of fish farmers and their establishments may not necessarily assure increased supply of fish products. However, the farms must be able to operate at their fullest production potential. Production efficiency-oriented studies for fish farming have been very limited in Malawi i.e., IAA adoption by Mussa [4], hence the concessional genesis of this study to estimate the level of technical efficiency (TE) of tilapia farms and evaluate the factors affecting farm efficiency. As stated earlier, most small-scale tilapia farmers use extensive to semi-intensive technologies, hence have low per unit productivity ranging from 500 to 2316 kg per ha [5]. The culture period is usually 6 months, and farmers have two crops per year as the average seasonal temperature according to Malawi Government [6] is 31°C in summer and 22°C in winter.

Conceptual framework

As reported by Fare et al., [7] and Farrell [8] technical efficiency is a major component of productivity which itself is a measure of farm performance. Ideally, technical efficiency indicates whether a farm uses the best available technology. It reflects the ability of a farm to obtain maximum output from a given set of inputs [9]. A technically efficient farm operates on the production frontier. A technically inefficient farm, i.e., one that operates below the frontier can achieve optimum efficiency either by increasing output with the same input-bundle or using less input to produce the same output. The closer a farm gets to the frontier, the more technically efficient it becomes.

Despite a system utilising all required inputs, there are many factors that can potentially bring inefficiency in aquaculture production. An individual's education affects his/her ability to allocate inputs cost-effectively, farmer's age, years in practice and exposure to technical information through trainings and interaction with extension workers are some of the core factors that affect a farm's technical efficiency through poor allocation of resources, and application of technological acumen.

Total tilapia production in Malawi and China is characteristically dependant on a number of input factors. Among the main factors are feed, seed, labour, manure/fertilisers and drugs. In general, feed is given twice a day in the morning and evening. Farmers also use fertilisers, especially animal manure to enhance primary productivity in their ponds to reduce feed application, as tilapia exhibit ontogenic feeding behaviour. In terms of seed, Malawian farmers use *Oreochromis shiranus,* which is an indigenous species and like all tilapia, the fish exhibit a number of drawbacks including early sexual maturity and unwanted reproduction [10-12] while for Chinese farmers, GIFT strain and the hybrid Ni ao (*Oreochromis niloticus* × *Oreochromis aureus)* are

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the two commonly cultured species [13], which have superior growth rate. As Govender [14] reports, labour is a measure of the work done by human beings. It is conventionally contrasted with such other factors of production as land and capital. Ideally, minimal labour is required to operate fish ponds, as adding more workers is not likely going to increase fish production. In the present study, the output variable was in the form of amount of tilapia in kgs produced per production establishment.

It is a general observation that resources in the fish farming industry in Malawi are being inefficiently utilized. The absence of quantitative research on technical efficiency is surprising; as there is a greater prospect of the tilapia sector improving its efficiency if determinants of technical inefficiency are isolated and estimated. As reported earlier on, there is little literature about efficiency estimates for fish farming in Malawi. Therefore, this study is expected to provide meaningful insights into the level of farm-specific technical efficiency along with factors affecting inefficiency. The present study focuses on small-scale semi commercial tilapia farmers in Malawi and compares their efficiency with tilapia producers in China. The study uses stochastic production frontier function by specifying the Cobb-Douglas model for technical inefficiency effects to obtain the empirical results hence determines the technical efficiency estimates and identify determinants of technical inefficiency for the farms.

Research Methodology

Study areas

This study was conducted in Malawi and China. Malawi has three seasons, and viz: the dry season running from August to October, the rainy season which stretches from November to April and the cool season which runs from May to July. The country's temperature and rainfall is mainly influenced by the lake and altitude, varying from 37 m in the Shire Valley Region, to 3050 m in the Mulanje Mountain area. Annual rainfall is between 635 mm and 3050 mm. Although rainfall varies, most parts of the country receive enough rain for dry land farming (except during periods of drought). The study was rather conducted in all the three administrative regions of: North, Centre and South. Farmers were sampled from the following districts: - Nkhatabay, Mzimba and Rumphi in the North, Lilongwe and Mchinji in the Centre and Zomba, Mangochi, Thyolo, Mulanje and Chikwawa in the South.

In China, the study was conducted in Guangxi Province. The Province is located in a sub-tropical region, where tilapia can be cultured and supplied all year round due to warm climate and rich rainfall [13]. Other advantages for tilapia culture in the province include: relatively long history of tilapia culture, good tilapia selection programs, well-developed large-scale tilapia hatcheries, well-trained researchers and extension workers [15]. The province also has tilapia processing factories that have been authorized by Hazard analysis of Critical Control Points (HACCP) and acquired accreditation for producing export quality products intended for the European Union (EU), USA and Japan markets, and this has also fostered the further expansion of tilapia culture in the province [15]. In 2014, the tilapia farming area in Guangxi comprised about 23,000 ha [16]. According to the China Fisheries Yearbook 2013-2014, tilapia production in Guangxi has increased by 10% on average between 2004 and 2013 against China's 7.16%, while contributing an averaged 16% to the total tilapia output.

Data collection

To generate economics data for Malawi, the study targeted 20 small-scale semi commercial fish farmers located in all the three regions of the country. The farmers were interviewed between December 2016 and February 2017 through administration of a structured questionnaire. Data and information collected include: sex, age, gender, marital status, education level, pond sizes, inputs (seed, feed, manure, drugs and labour), number of ponds owned, production level and pricing (farm gate prices, factors affecting pricing). Oral informed consent was obtained from each study participant before commencement of the interview, as the enumerator briefly explained the purpose of the study, the risks and benefits of participation in the study, and conditions of confidentiality. As reported by Ahmed et al. [17], participatory, qualitative, and quantitative methods were combined in the primary data collection.

For China, secondary data from Guangxi Province, which was collected in 2014 was used. A random sampling survey was employed to identify the target farmers and data was collected through administration of structured questionnaires by a team of enumerators. Data exploration was therefore done to screen and organize the secondary data for identification of 20 small scale tilapia farmers to be part of the present study. Among the factors considered in the data exploration were identifying those famers that met the study criteria by having all above-mentioned study parameters for inputs, output and marketing data. However, Chinese farmers did not have data on manure for pond fertilisation, but inversely they had electricity as an input of production.

Data analysis

For better comparative analysis of the two production systems, efficiency estimates [8] rather than effectiveness measures were used. Stochastic Production Frontier (SPF) approach [18-20] is one of the efficiency estimate models that have been employed in recent studies [21-25] have employed the FRONTIER 4.1 software, and used [26], to simultaneously estimate the parameters of the SPF and the TE models. The stochastic production frontier and technical inefficiency models have been widely used in determining farm-level efficiency in developing countries' agriculture since the publication of a seminal article of Farrell [8] on efficiency measurement and subsequent development of several approaches to efficiency and productivity measurement. The most basic method of TE is to map a production frontier (statistically or non-statistically, parametrically or non-parametrically), find the locus of maximum output levels associated with given input levels and estimate farm-specific TE as a deviation from the fitted frontier.

Among different major approaches followed to measure and estimate efficiency, the stochastic production frontier (SPF) approach involving econometric estimation of parametric function [18-20] and nonparametric programming, known as data envelopment analysis (DEA) [27], are the most popular. The stochastic frontier is considered more appropriate for assessing TE in developing countries' agriculture production, where the data are often heavily influenced by measurement errors and other stochastic factors such as weather conditions, diseases, etc. [7,9,22-23,28-30]. Several recent studies have applied stochastic frontier technique for determining efficiency in aquaculture in the developing Asian countries [21,23-25,31-35] and African countries [4,36-40].

There are two approaches to analyse determinants of TE or inefficiency. A number of authors first estimated stochastic frontiers to predict firm-level efficiencies and then regressed these predicted efficiencies upon farm-specific variables (such as managerial experience, ownership characteristics and production conditions) in

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an attempt to explain variations in output between firms in an industry [41,42]. This is usually referred to as a two-stage procedure. Several economists have however criticised this procedure [43-45] arguing that the socioeconomic variables should be incorporated directly into the estimation of production frontier model because such variables may have a direct influence on the production efficiency. To overcome inconsistencies in the assumptions regarding the independence of inefficiency effects in this two-stage estimation procedure, Kumbhakar et al. [44] and Reifschneider and Stevenson [45] proposed a single-stage stochastic frontier model in which the inefficiency effects (u_i) are expressed as an explicit function of a vector of farm specific variables and a random error.

Nevertheless, in spite of the criticisms, many studies have used two-stage approach; Simar and Wilson [46] have mentioned of about 800 published articles and working papers that have followed two-stage approach for measuring efficiency. This study however, employed the single-stage stochastic frontier model in estimating farm TE and its associated inefficiency factors. The parameters were estimated using the following formulas and functions. The SPF with two error terms was modelled as:

$$Y_i = f(X_i\beta)\exp(V_i\text{-}U_i) \quad (1)$$

Where Y_i is the production of the i-th farm (i = 1,2,3.............n), X_i is a (1 x k) vector of functions of input quantities applied by the i-th farm; β is a (k x 1) vector of unknown parameters to be estimated, $V_i s$ are random variables assumed to be independently and identically distributed as $N(O,\delta^2_v)$ and independent of $U_i s$ and the $U_i s$ are non-negative random variables, associated with technical inefficiency in production assumed to be independently and identically distributed as truncation (at zero) with mean $Z_i\delta$ and variance σ^2_u (U~|N(Z$_i\delta$, σ^2_2)|); Z_i is a (m x 1) vector of farm specific variables associated with technical inefficiency, and δ is a (m x 1) vector of unknown parameters to be estimated [47].

Following [26], the technical inefficiency effects U_i in equation (1) was expressed as:

$$U_i = Z_i\,\delta + W_i \ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

Where W_i are random variables defined by the truncation of the normal distribution with zero mean and variance σ^2_u such that the point of truncation is at $Z_i\delta$, i.e. $W_i \geq -Z_i\delta$.

The maximum likelihood estimates (MLE) of the parameters of the model defined in equations (1) and (2) were estimated using the Frontier 4.1 package [48]. The efficiencies are estimated using a predictor that is based on the conditional expectation of *exp (-U)* [48,49]. In the process, the variance parameters σ^2_u and σ^2_v are expressed in terms of the parameterization:

$$\sigma^2 = \left(\sigma^2{}_u + \sigma^2{}_v\right) \ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

and

$$\gamma = \left(\sigma^2{}_u / \sigma^2\right) \ldots\ldots\ldots\ldots\ldots\ldots \quad (4)$$

The value of γ (Equation 4) ranges from 0 to 1, with values close to 1 indicating that random component of the inefficiency effects makes a significant contribution to the analysis of the production system [50].

Model Specification

A number of functional forms exist, that have been developed to measure the physical relationship between inputs and output. The most common form in practice is the Cobb-Douglas (CD). The stochastic production frontier for tilapia farming in Malawi and China was therefore estimated using the Cobb–Douglas functional form as specified below:

$$InY_i = \beta_0 + \sum_{k=1}^{n} \beta_k InX_{Ki} + V_i - U_i \ldots\ldots\ldots\ldots \quad (5)$$

Where subscript i refers to the ith observation in the sample (i = 1,2,3….20); ln represents the natural logarithm; β_o, β_k are parameters to be estimated. Y is observed farming system output (expressed in kg). X_i represents the total number of tilapia fingerlings stocked, X_2 is the total amount of feed used in the production cycle (expressed in kg), X_3 is the total cost of manure and fertilizer applied (expressed in USD), X_4 is the total value of drugs (including lime) applied by the farmer (expressed in USD), X_5 is the total cost of electricity used (expressed in USD), X_6 is the total value of labour used during the production cycle (expressed in USD) and V_i and U_i are noise and inefficiency respectively.

Results

Sample characteristics

Table 1 presents the measurement of output and input variables in the SPF and technical inefficiency model, while Table 2 gives the summary statistics of the relevant variables for tilapia farmers in the two countries. The table reveals that considerable variation exists among the farms in terms of production practices and the socio-economic attainments of the farmers within their respective countries. Mean output from Malawian farms was 524.51 kg, ranging from a minimum of 120.23 kg to as high as 2184.00 kg. Main inputs of feed, labour and seed cost were USD348.86, USD197.46 and USD89.69 respectively. Cost of drugs and manure were USD26.15 and USD17.17.304. For inefficiency factors, age averaged 53.95 years which was within a range of 84 and 31, while households had an average of 5.5 people, with most of the farmers having gone beyond high school education (2.35), apart from having 4.8 years of experience. Pond sizes were averaged at 1082.95m². Chinese farmers registered a mean output of 976.76 kg with a minimum of 722 kg and a maximum of 1190.48 kg per mu. Seed input was 2039.33, while feed used was 1334.11 kg. Other inputs were drugs, electricity and labour with costs of USD12.80, USD21.84 and USD65.84 respectively. Technical inefficiency factors included age 47.65 years, household size averaged 1.85 people while education was at 3.60 with most farmers attaining primary education, and the farmers had mean experience of 9.55 years.

Variables	Description	Unit
Y	Total tilapia production for the sample farms	Kg
	Variables in the production frontier	
X_S	Number of fingerling stocked in ponds	--
X_F	Amount of feed used	Kg
X_M	Cost of manure applied	USD[a]
X_D	Cost of drugs applied	USD[a]
X_E	Cost of electricity used	USD[a]
X_L	Cost of labour employed	USD[a]
	Variables in the inefficiency function	
Z_{AGE}	Age of tilapia farmers	Years
Z_{HHS}	Household size of farmers	Years
Z_{EL}	Education level (1= University, 2= College, 3= High, 4= Primary, 5= None)	
Z_{AE}	Experience of tilapia farmers in aquaculture	Years
Z_{PS}	Pond size	M²
[a]USD1 = K724.45 = 6.67 ¥		

Table 1: Measurement of output and input variables in the SFPF and technical inefficiency model for tilapia farmers in Malawi and China.

Hypotheses testing

The sigma squared (σ^2) which is an indication of goodness of fit was statistically significant at 5% level (Table 3), showing the goodness of fit of the survey data from both countries with the model used and the correctness of the specified coefficients. To test the null hypothesis that there was no significant technical inefficiency hence observed variations in TE estimates were simply random or systematic ($H_0 = 0$), an estimated γ parameter, which measures the variability of the two sources of error was statistically significant at 1%, hence it was suggested that 99% of the total variation of total production were related to inefficient error term and 1% of the total variations attributed to stochastic random errors. This implies that the variation of the total production among the different tilapia farms in both countries was due to the differences in their production inefficiencies.

Technical efficiency estimates and inefficiency factors

Table 3 presents respective individual coefficients and the corresponding t-ratios for the stochastic production frontiers for the two farming categories. For Malawian farms, all the elasticity of production except for the labour coefficient have the expected a priori positive sign. For Chinese farms, all the production coefficients have positive contribution towards the production frontier.

In the present study, results of technical inefficiency estimates show that all determinants of inefficiency except aquaculture experience had positive signs for the Malawian farms even though none of the coefficients was significant. For Chinese tilapia farmers, age (significant), household size and education had negative signs except aquaculture experience which was positive.

Technical efficiency distribution

For a clearer indication and understanding of the distribution of technical efficiencies among tilapia farmers in the two countries, the frequency distributions of the estimated efficiencies are plotted in Figures 1 and 2. The results show that 65% of tilapia farmers in Malawi had technical efficiency scores of less than 50%, while 70% of farmers in China were producing at above 90% efficiency. Only 5% of Malawian farmers were above 90% technically efficient.

Name of variables	Mean	Max	Min	SD
Malawi				
Expected Yield (kg)	524.51	2184.00	120.23	572.34
Seed	6773.70	21000.00	1452.00	4422.83
Feed (kg)	425.00	900.00	150.00	200.82
Manure cost (USD)	17.17	41.41	3.04	9.49
Drugs/lime cost (USD)	26.15	71.78	9.13	17.26
Labour (USD)	197.46	628.06	45.63	155.68
Age (years)	52.95	84.00	31.00	14.71
HH size	5.50	8.00	4.00	1.36
Education	2.35	4.00	1.00	1.14
Experience (years)	4.80	13.00	1.00	3.27
Pond size (m^2)	1082.95	3500.00	400.00	683.62
China				
Expected Yield (kg)	976.76	1190.48	722.22	116.75
Seed	2039.33	2800.00	1100.00	512.89
Feed (kg)	1334.11	1771.48	922.65	231.08
Electricity (USD)	12.80	20.61	5.00	3.38
Drugs/lime (USD)	21.84	74.96	3.75	16.16
Labour cost (USD)	65.84	110.05	22.63	27.88
Age (years)	47.65	70.00	36.00	7.55
HH size	1.85	5.00	1.00	1.04
Education	3.60	4.00	2.00	0.60
Experience (years)	9.55	22.00	1.00	5.74

Table 2: Summary statistics of the variables.

Variable	Parameter	Malawi		China	
		coefficient	t-ratio	coefficient	t-ratio
Production frontier					
Constant	β_0	-1.174	-0.648	3.227***	3.480
X_S	β_1	0.065	0.249	0.015	0.135
X_F	β_2	1.403***	4.279	0.434***	3.031
X_M	β_3	0.188	1.468	--	--
X_D	β_4	0.017	0.061	0.144***	3.437
X_E	β_5	--	--	0.035**	2.430
X_L	B_6	-0.311	-1.574	0.010	0.265
Inefficiency function					
Constant	δ_0	0.857*	1.855	0.891***	3.414
Z_{AGE}	δ_1	0.001	0.131	-0.013**	-2.288
Z_{HHS}	δ_2	0.065	1.180	-0.006	-0.102
Z_{EL}	δ_3	0.049	0.515	-0.072	-1.236
Z_{AE}	δ_4	-0.049	-1.221	0.000	0.047
Z_{PS}	δ_5	0.000	-1.149	--	--
Variance parameters					
Sigma-squared	σ^2	0.064**	2.568	0.009**	2.558
Gamma	γ	0.999***	16.577	0.999***	7.136
Log likelihood	--	0.160	--	0.299	--
LR test	--	10.682	--	12.207	--
TE estimates					
Mean		46.75%		91.26%	
Max		100.00%		99.83%	
Min		22.00%		69.20%	
SD		20.42		7.77	
Skewness		1.40		-1.42	
*** Significant at 1%, ** Significant at 5%, * Significant at 10%					

Table 3: Maximum-likelihood estimates of the SFPF and inefficiency function.

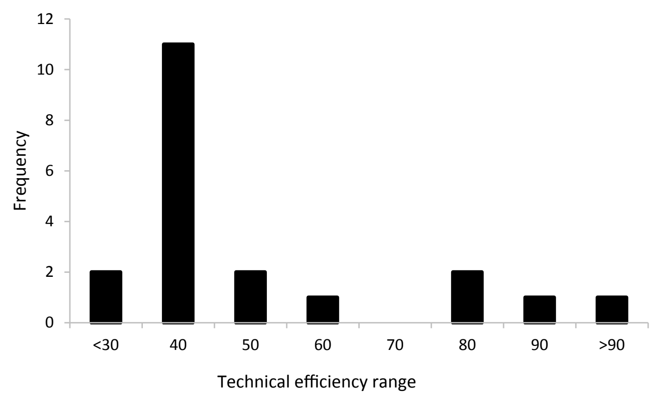

Figure 1: Distribution of technical efficiency estimates for Malawi farms.

Discussion

Results of the Cobb Douglas model indicate that with a positive sign in most coefficients, *ceteris paribus* an increase in a particular input will result in an increase in yield. With respect to seed (fingerlings), manure and drugs the elasticity of output was not statistically significant. However, the results show that the elasticity of output with respect to feed was statistically significant, hence for a 10% increase in fish feed,

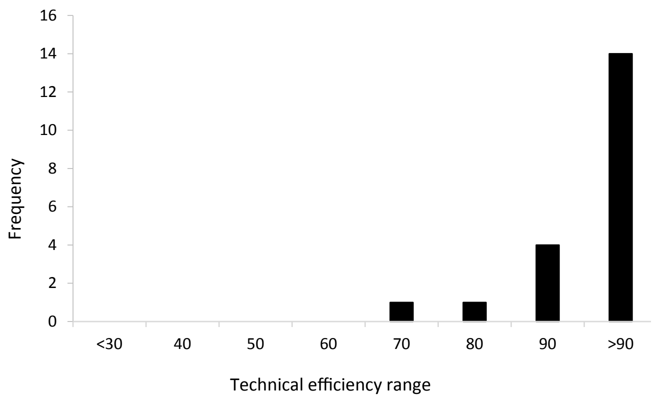

Figure 2: Distribution of technical efficiency estimates for China farms.

production is expected to increase by 14% in Malawi, and 4.34% in China farms. Apart from feed, coefficients of drugs and electricity for China farms had statistical significant effects, hence 10% increase in these inputs is expected to contribute an increased yield of 1.44 and 0.35% respectively. A marginal 10% increase in manure and drugs in the production of tilapia in Malawi, could result in a yield increase of 1.88 and 0.17% respectively. Furthermore, an insignificant change is expected with a 10% increase in seed 0.65% (Malawi) and 0.15% (China). This is in agreement with Akenbor and Ike [40] who found that technical efficiency was significantly and positively influenced by stocking rate in catfish farming in Edo, Nigeria. However, the results are in disagreement with Tung [51], who reported a negative relationship between stocking density and technical efficiency for shrimp in Vietnam. For an increase in labour, it is expected that production will decrease in Malawi by 0.49% which is in agreement with [34], and an insignificant increase of 0.0005% in China farms.

Just like Alam et al. [25] observes, age of farmers was a significant determinant of technical inefficiency for Chinese farms. However, it had significant positive influence on technical efficiency as was in Dey et al. study [22] and Zhang et al. study [52], conversely it had insignificant negative influence for Malawian farms, which was similar to earlier findings by [35] in a study on prawn farming in Vietnam. Household size which is credited to contribute to availability of farm labour had a non-significant but negative influence on inefficiency for Chinese farms, hence it positively influenced efficiency. Furthermore, the factor negatively influenced technical efficiency for tilapia farms in Malawi. Results of the present study further show that education coefficient has a positive sign, for Malawi, and negative for China. Since the factors were coded in descending order 5 (no education) and 1 (University education), the results signify a positive influence on efficiency for Malawian farmers, which was similar to findings by Tung [51] and Dey et al. [22]. Education can enhance production in that the higher a farmer goes with education, the better he becomes in assessment of the importance of new technologies, as well as the efficient use of inputs. Besides, education improves the managerial capacity of a farmer, which consequently leads to significantly higher efficiency. However, increased education will result in reduced technical efficiency for Chinese farmers, which is in agreement with findings by Chiang et al., Akenbor and Ike and Khan and Alam [34,40,53].

The coefficient of aquaculture experience though insignificant, positively influenced technical efficiency in Malawian farms which was also reported in earlier studies by Den et al., Tung, Kaliba and Engle [35,51,54] but had negative influence on the technical efficiency of tilapia farms in China. With an average of 9.55 years of experience, any marginal year increase in experience could result in highly insignificant recession in efficiency for Chinese farmers, which was in agreement with [34,53,52]. For Malawi, pond size was found to have a positive but insignificant influence on technical efficiency. The result supports earlier findings by Tung, Penda et al., Huy, Alam and Murshed-e-Jahan, and Ogundari and Ojo [51,55-58].

Conclusion and Recommendations

In this study; "technical efficiency of tilapia production in Malawi and China", the study has revealed that most of the farmers in China operate at above 90% technical efficiency, while about 65% of Malawian farmers are technically inefficient, with an average technical efficiency of 47%, hence have 53% room on average, within which they can improve. Thus, the farmers in Malawi have the potential to increase yield per hectare from the current average of 4152.60 kg to 8714.80 kg. Malawi needs technology innovations in order to reduce this 53% yield gap, which can ideally be introduction or development of new strains of superior quality, enhanced use of all-male tilapia and improvement in both nursing and grow-out technologies. Just as it has been observed that very few farmers operate at above 90% efficiency, enhanced farmer to farmer contact i.e., full rollout of *lead farmer initiative* to enhance information sharing can help in motivating other farmers whose performance is low in order to improve the way they use resources in their tilapia farming operations. The significant positive constant coefficient of inefficiency function shows that there are inefficiency effects in tilapia production in Malawi, therefore there are possibilities for improving the performance as evidenced by the variations in the standard deviation range of efficiency scores from the mean technical efficiency. Finally, the highly statistical significant and positive sign of feed coefficient signifies that feed input is key to improved tilapia production in Malawi, so subsidised formulated feed has the potential to change the aquaculture production landscape. However, with education having positive influence on production elasticity, more aquaculture development programmes might yield tangible results if the target beneficiaries are people with formal education. For Chinese farms, the 9% average yield gap can be reduced by improving the resource-use efficiency of feed.

Conflict of Interest

The authors declare that they have no conflict of interest.

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