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Does Charco-Dam Technology Affect Production Efficiencies? Evidence from Small-Scale Vegetable Farmers in Nzega District, Tanzania

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Abstract

Water for irrigation is an essential and primary factor influencing crop productivity. However, there is limited information on how availability of irrigation water guarantees efficient use of inputs in farm production, especially for the rainwater harvesting technologies managed at household level. This study employed survey method to collect data from 528 small scale vegetable farmers, randomly selected from 5 wards and 5 villages, among the farmers 220 were adopters of Charco-Dam Technology (CDT) and 308 were non-adopters. Technical Efficiency Model was used to estimate production efficiencies of 528 small-scale vegetable producers, and Propensity Score Matching (PSM) Approach employed to evaluate the influence of adopting charco-dam technology on the production efficiencies of these farmers located in Nzega district, Tanzania. Results from the analysis present the essential intuitions about adoption of CDT and its effects on production efficiencies. It was observed that there was inefficient use of inputs (land-size, labour, quantity of improved seeds, amount of chemical used and amount of fertilizer used) among small-scale vegetable producers in the study area.

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The inefficiency was basically observed to be caused by household-size, cost of farm labour as well as growing cabbages and scarlet-eggplants. It is further observed that, farming experience, number of farm workers and radio listening behaviour reduced technical inefficiency (i.e., improve technical efficiency). Further analysis using PSM method, found that the adopters of charco-dam technology in the study area significantly increased the efficient use of inputs as compared to non-adopters, and hence realised high yields. This study recommends that, technologies like charco-dam should be encouraged, especially to small-scale farmers in arid and semi-arid areas. Furthermore, experienced farmers should share expertise on the use of inputs, with other less experienced farmers. In line with this, the role of agricultural information on improvement of production efficiency should not be undermined in improving efficient use of inputs. Hence, programmes and intervention that focus on encouraging farmers to listen to radio programmes related to agriculture, particularly those covering specific crop and location, are recommended.

Keywords

Charco-Dam Technology – production efficiencies – technical efficiency – propensity – score matching – small-scale vegetable farmers

1 Introduction

Water has been an important aspect to facilitate production in all kinds of agricultural production. Any technology that leads to water availability at farm level especially in the arid and semi-arid areas is highly appreciated by farmers (Bouma et al., 2011; Biazin et al., 2012; Bell et al., 2015). Charco-Dam Technology (CDT) is one of the important traditional small-scale rain water- harvesting technologies in many arid and semi-arid areas (Nissen-Petersen, 2006; Mati, 2015). The technology can be a large catchment and managed by community (community-based ownership) or a small catchment managed by individual farmers, mainly used for farming activities. CDT is earth excavated pan, pit or pond, which is constructed at well-selected sites on a relatively flat topography, usually receive their runoff mostly from outlying areas of a rangeland, thus contour bunds are constructed to divert runoff into the dam and can collect over 10,000 m^3 of water (depending on the catchment area) and having the embarkments which reaches a height of over 5 meters. The design of the charco-dam is simple and can be implemented at village level with minimum of engineering requirements using animal draught, farm tractor, a crawler or

bulldozer (Wagner, 2005; META, 2015). One of the advantages of CDT is timely availability of irrigation water and flexibility of what to produce at a particular time given the available market. With such convenience, the technology is assumed to have the potential of transforming subsistence farming into commercial production, which can eventually improve wellbeing of small-scale farmers, especially in arid and semi-arid areas.

In Tanzania, CDT has been adopted in several arid and semi-arid areas, including; Shinyanga, Dodoma, Arusha, Tabora, Singida and Mwanza regions, for both crops irrigating and livestock watering (Hatibu et al., 2000). However to some areas the water are used for domestic consumption, and is differentiated from one area to another based on the water-use, management level, size as well as shapes of the facility, this is mainly due to socio-economic status of the people in particular area (Hatibu et al., 2000; Barron et al., 2009). Unlike other regions in Tanzania, where charco-dams are owned and managed by community or group of people, CDT in Nzega are owned and managed mostly by individuals mainly for crop farming. This is due to the challenges brought by the communal managed and controlled water sources, which include limited frequency and amount of water accessed, and to some catchments limitation on the type of crop to cultivate. This unique characteristic is believed to overcome water management and control issues, as the production decision is purely based on one decision maker (owner of the irrigation facility) and not majority in the community, but also is expected to improve production efficiency of the technology adopters.

So far, various studies in East Africa and Tanzania in particular have been provided information on the best practices based on; typologies, designs, profitability, and affordability of various RWH techniques that are managed (Nissen-Petersen, 2006; Rwehumbiza, 2007; Mahoo et al., 2007; AgWater Solution, 2010; Studer and Liniger, 2013). However, there is limited information on how availability of irrigation water guarantees efficient use of inputs in farm production, especially to the RWH managed at household level. Production efficiency is an important tool to measure farmers' performance, which can be evaluated through improved production levels measured by farm productive efficiencies. The concept can be better understood through evaluating production decisions and the levels of technical efficiency. The evaluation is to safeguard the economic viability and farm sustainability (Ahmadzai, 2017).

Technology adoption such as use of new machinery, chemicals, fertilizer and improved seeds, is directly associated with improved farm productivity which is also directly related with the improved technical efficiencies (TES) (Abdulai et al., 2011; Asante et al., 2014). On the other hand, productivity can be enriched by changing the combination of the factors mentioned, through

improved efficiency of the technology used (Coelli, 1995). Inefficiency at farm level productivity in developing economies is mainly caused by failure of the farmers to fully exploit production technologies and production resources. It is further argued that the inefficiency is normally due to factors related to socio-demographic characteristics of households, farm characteristics as well as the structure of organizations that the individual farmers are associated with (Musaba and Bwacha, 2014; Selejio et al., 2018).

This study employed Technical Efficiency (TE) Model together with the Propensity Score Matching (PSM) Approach to come up with facts to explain the influence of adopting CDT on production efficiencies. TE models have mostly been used in determining farm and production technical efficiencies of various crops and agricultural technologies (Maffioli et al., 2013; Musaba and Bwacha, 2014; Asante et al., 20142; Ahmadzai, 2017; Selejio et al., 2018). On the other hand, PSM has widely been used in experimental studies to measure conditional independence and in dealing with confoundedness assumption as well as to effectively address the problem of self-selection bias inherent in choice problems in observational studies like this one (Ho et al., 2007; Austin, 2011; Li, 2013a; Brazauskas and Logan, 2016). Hence, blending the two approaches provides more consistent and reliable analysis of the effects of adopting CDT on production efficiencies.

2 Research Design, Sampling and Data Collection Methods

A survey design was used to gather the required information from small-scale vegetable farmers in Nzega District. The district is one of the seven districts of Tabora Region in Central Tanzania, receives annual rainfall between 650 mm and 850 mm, with the annual temperature ranging between 28 to 30°C,[1] while October and July are the warmest and coolest months, respectively.

Such rainfall pattern and temperature extremes make the district one of the hottest and driest districts in the region; which is distinguished as a tropical savanna climate and typically pronounced by a dry season, or mostly referred to as semi-arid.

The survey involved 528 small-scale vegetable farmers, 1 district, 5 wards and 5 villages were purposefully selected. The criteria for selection were based on the presence of CDT and the nature and type of crops cultivated (vegetables for this case). Through respective ward and village extension officers,

1 www.tabora.go.tz The United Republic of Tanzania President's Office Regional Administration and Local Government (PORALG), Tabora Regional Administrative Secretary.

TABLE 1 Population and sample

Name of village	Total vegetable producers	Sampled vegetable producers	Respondents used for analysis	
			CDT adopters	CDT non- adopters
Itunda	102	81	30	46
Ikindwa	138	103	39	62
Shila	152	110	47	63
Busondo	173	121	44	76
Iyombo	184	126	60	61
Total	749	541	220	308

small-scale vegetable producers in each village were identified, and the lists comprised both adopters and non-adopters of the CDT were developed in each village, formula of Yamane (2001) was used to determine required number of farmers in each village (Table 1). Lastly, randomly selection was done to obtain the number of respondents selected from each village (220 adopters and 308 non-adopters). Respondents were interviewed using a structured questionnaire, and a total of six focused group discussions (FGDs) were conducted; one at council headquarters and five at village level, to validate and substantiate the information collected during survey.

3 Estimating Technical Efficiency

The ability of a firm to produce as large as possible an output from a given set of inputs is generally referred as production efficiency (Kumbhakar & Lovell, 2000). In estimating the Technical Efficient (TE), both parametric and non-parametric approaches can be used to measure the levels of Technical Efficiencies. Ignoring the specification of function form is the advantage of using non-parametric approaches (Charnes et al., 1978). However, inability to account for stochastic error has made the generated technical efficiency scores using non-parametric methods to be lower than those estimated using parametric approaches, hence to some cases lead to bias estimates (Coelli, 1995; Kumbhakar and Lovell, 2000; Ahmadzai, 2017). On the other hand, parametric approaches are based on econometric theory, whereby the deviation of the production frontiers is not controlled by an individual, and it accommodates

both the effects of statistical noise and effects of the inefficiency factors (Aigner et al., 1977; Battese and Coelli, 1995; Qu et al., 2020). Allowing hypothesis testing and construction of confidence intervals with the assumption that all firms share the same production technology and face similar environmental condition is one of the key advantages of using parametric approaches in estimating production frontiers (Bravo-Ureta and Evenson, 1994; Wadud and White, 2000; Dolisca and Jolly, 2008). However, the approaches have remarkable drawbacks as they require functional form specification for the frontier technology and for the distribution of technical inefficiency term of the error term (Aigner et al., 1977; Wadud and White, 2000). Basing on the nature of the study and advantages of parametric approach over non-parametric approach, Stochastic Frontier Analysis (SFA) was used to obtain production efficiencies of adopters and non-adopters of CDT.

Following the works of Aigner and Chu (1968), Afriat (1972), and Richmond (1974), and as explained in Aigner et al. (1977), this study is assumed a deterministic maximum possible output function given a certain inputs as specified by the following equation:

$$A_i = f(X_i;\beta) \ldots \ldots i = 1,2, \ldots, N \tag{1}$$

whereby A_i is output, X_i is the vector of inputs, β is the parameter to be estimated, and N represent number of observations, which is simply estimated using mathematical programming by minimizing $\sum_i^N [A_i - f(X_i;\beta)]$ for linear production function and $\sum_i^N [A_i - f(X_i;\beta)]^2$ for quadratic (non-linear) production function, subject to $A_i \leq f(X_i;\beta)$.

However, according to Aigner et al. (1977) the estimation do not lead to estimates with known statistical properties, as in reality farmers are potentially producing less than what they might produce due to inefficiencies caused by various social-economic variables. Thus, the proper equation becomes

$$A_i = f(X_i;\beta)\, TE_i \ldots \ldots i = 1,2, \ldots, N \tag{2}$$

whereby the TE_i is the level of technical efficiency of farmer i, while the meaning of the rest of the terms remained as in equation (1). The interval of technical efficiencies (TES) is between 0 and 1, if $TE = 1$ an individual is at optimal output level given the technology, while anything less than one, an individual is not making the most out of inputs invested given technology, thus degree of technical efficiencies (TES) is usually assumed to be strictly positive (i.e., $TE_i > 0$).

4 Estimating Effects of Charco-Dam Technology on Technical Efficiency

This study assumed that, adoption of Charco-Dam Technology (CDT) has the potential of impacting farmers' productivity through improved technical efficiency. Analyzing technical efficiency assists to determine whether the existing technology should continue adopted or needs some improvements to realize improved productivity. Technical efficiency was estimated using equations (1) and (2). Further, the average treatment effect of adopting CDT on technical efficiency of the treated (ATT) was estimated by Propensity Score Matching (PSM). The study assumed *"treatment"* to be the adoption of charco-dam technology (CDT); the *"treated"* being individual small-scale vegetable farmers, and; the *"effect"* is the change in the efficiency use of inputs (measured by the increase or decrease in the technical efficiency scores) for the farmers who adopted the CDT. So, the ATT model was denoted as

$$ATT = E(y_{1i} - y_{0i}|A_i = 1) = E(y_{1i}|A_i = 1) - E(y_{0i}|A_i = 1) \quad (3)$$

whereby y_{1i} and y_{0i} are the potential outcomes in the two counterfactual situations of treatment and no-treatment, respectively, $E(\cdot)$ expected value of adopting CDT, such that $A_i = \{0,1\}$. Various literature have suggested a number of matching algorithm (Becker and Ichino, 2002; Sainani, 2012; Stone and Tang, 2013; Brazauskas and Logan, 2016; Jacovidis, 2017; Qu et al., 2020). Given the fundamental objective of the study which is to measure the effect of CDT on TE, then two matching estimators, that is the Nearest Neighbour Matching (NNM) and Kernel Matching Method (KMM) were used for this analysis. NNM is the most straight forward estimator, basically it computes the ATT by selecting n comparison units whose propensity scores are nearest to the treated unit in question, meaning that the outcome of the control units matches with the outcome of the treated units only when the propensity scores fall in the predetermined radius of the treated unit, thus can also referred as radius matching (Caliendo and Kopeinig, 2008; Li, 2013). While, KMM uses weighted average of all controls obtained by distance of propensity score, bandwidth parameter, and Kernel function. According to Li (2013) these aspects can be specified by Gaussian Kernel. The algorithms used to estimate NNM and KMM are as follows:

$$ATT_{NN} = \frac{1}{N^T}\sum_{i=1}^{N^T} Y_i^N - \frac{1}{N^T}\sum_{j=1}^{N^C} \varpi_j Y_j^c \quad (4)$$

$$ATT_{KM} = \frac{1}{N^T}\sum_{i=1}^{N^T}\left\{Y_i^T - \frac{\sum_{j=1}^{N^C} Y_j^C K\left(\frac{e_j(x)-e_i(x)}{h_n}\right)}{\sum_{k=1}^{N^C} K\left(\frac{e_k(x)-e_i(x)}{h_n}\right)}\right\} \quad (5)$$

whereby ATT_{NN} = Average Treatment of Treated using Nearest Neighbour, N^T = Number of individuals in treated group (adopters), Y_i^T = Outcome of individuals in treated group, N^C = Number of individuals in control group (non-adopters), Y_j^C = Outcome of individuals in control group, ϖ_{ij} = weights, where $\varpi_j \in [0,1]$ *and* $\sum_{j=1}^{N^C} \varpi_j = 1$, ATT_{KM} = Average Treatment of Treated using Kernel Matching, $e_j(x)$ = propensity score of jth individual in the control group, $e_k(x)$ = propensity score of ith individual in the treated group, $e_j(x) - e_i(x)$ = distance of propensity scores, h_n = bandwidth parameter, and $K(\cdot)$ = kernel function.

5 Results of the Analysis

5.1 *Descriptive Analysis*

Generally the surveyed small-scale vegetable farmers in the study area observed to cultivate an average of 2.38 acres of vegetables per season (12 months). It was further noticed that, these farmers used an average of 1477.29 grams of improved seeds, 695.09 kilograms of fertilizers and 695.09 liters of chemicals to produce an average of 1323.25 kilograms of vegetables. Most of the surveyed vegetable farming households are male (87%) and attained formal education (84%). These farmers have an average of 24 years of experience in farming, and having an average of 5.11 household size. Moreover, 39% of these farmers have accessed micro-finance schemes in 12 months, 50% have a radio-listening behaviour, using an average of 5.27 people for farm-labour, using an average of 78190.74 TZS to pay the labour force. Out of 528 farmers, 25% cultivated tomatoes, 10% cultivated cabbages, 28% cultivate sweet-peppers, 18% cultivated scarlet-eggplants and 41% cultivated leafy-vegetables, as their main cash-crop (Table 2).

5.2 *Test Results for Required Production Functional Form*

Test results of the functional form and the presence of inefficiency in the production model using stochastic production frontier are presented in Table 3. Unrestricted and restricted analyses for Cobb-Douglass and Trans-Log production functions were estimated and likelihood-ratio test was conducted using

TABLE 2 Descriptive analysis of variables used in (In) efficiency model (n = 528)

Variables	Mean	SD	Min	Max
Crop yield (kg/acre)	1323.253	918.7364	104.17	6,000
Land-size (acre)	2.38	1.24	1	6.5
Amount of seeds (grams)	1477.29	1,767.63	100	22,000
Amount of fertilizer (kg)	695.09	524.98	25	1,850
Amount of chemicals (liters)	347.6362	354.0226	0	1,880
Sex of household head (1 if male, 0 if female)	0.87	0.34	0	1
Education level of household head (value 1 if attained formal education, 0 if did not)	0.84	0.36	0	1
Farm experience (years)	24.30	11.52	3	66
Household size	5.11	2.09	1	10
Member of micro-finance scheme (1 if yes, 0 if no)	0.39	0.48	0	1
Radio listening behaviour (1 if yes, 0 if no)	0.50	0.50	0	1
Total farm-labour	5.27	1.91	1	12
Cost of farm-labour (TZS per year)	78,190.74	161,908.9	0	845,000
Tomatoes (1 if yes, 0 if no)	0.25	0.43	0	1
Cabbages (1 if yes, 0 if no)	0.10	0.30	0	1
Sweet-peppers (1 if yes, 0 if no)	0.28	0.45	0	1
Scarlet-eggplants (1 if yes, 0 if no)	0.18	0.38	0	1
Leafy-vegetables (1 if yes, 0 if no)	0.41	0.49	0	1

equation $LR = -2[ln\{L(H_0)\} - ln\{L(H_1)\}]$, where $L(H_0)$ and $L(H_1)$ are values of likelihood functions under the null (H_0) that there is no technical inefficiency in the models among sampled vegetable producers, versus the alternative (H_1) that, there is a technical inefficiency among the producers. Using Stata statistical software the test statistics were computed and compared with critical values as provided by Kodde and Palm (1986) and form chi-square table. The results show that, both models (Cobb-Douglas and Trans-Log production functions) rejected the Null Hypothesis that, there is no technical inefficiency among small-scale vegetable producers at 1% significant level. This implies

TABLE 3 Model specification test

Model	Log-likelihood	Calculated LR-statistics	Critical χ^2 at 1%	Decision
Test of presence of inefficiency; Null Hypothesis (H_0): There is no technical inefficiency among small-scale vegetable farmers				
Cobb-Douglass Production Frontier				
Restricted Model	−308.60676	142.15696	34.167	Reject H_0
Unrestricted Model	−237.52828			
Trans-Log Production Frontier				
Restricted Model	−225.29776	154.88026	54.172	Reject H_0
Unrestricted Model	−147.85763			
Null Hypothesis (H_0): Cobb-Douglass Production Frontier is not appropriate to measure technical inefficiency among small-scale vegetable producers over Trans-Log Production frontier				
Cobb-Douglass Vs Trans-Log Production Frontier Models				
Unrestricted Cobb-Douglass Production Frontier Model	−237.52828	179.3413	77.386	Reject H_0
Unrestricted Trans-Log Frontier Model	−147.85763			

Note: Critical χ^2 values were taken from Kodde and Palm (1986), and from chi-square table; Calculated χ^2 were obtained from log likelihood functions. Restricted models are those assuming error term is due to random shocks (i.e., conventional production functions) and Unrestricted models are those assuming inefficiency effects as explained by Aigner et al. (1977).

that both functional forms, i.e., Cobb-Douglas and Trans-Log production functions shows the existence of technical inefficiency among the surveyed farmers. However, further analysis was conducted to compare between Cobb-Douglas Stochastic Frontier and Trans-Log Stochastic Frontier, which one fits the best. The Likelihood Ratio Test was conducted for Unrestricted Cobb-Douglass Production Frontier and Unrestricted Trans-Log Production Frontier. The results show that, the calculated LR statistics (calculated chi-square) for Unrestricted Cobb-Douglass Production Function was higher than that of critical chi-square at 1% level of significance. This give a strong reason to reject

the set null hypothesis, meaning that the alternative is accepted, that, Cobb-Douglass Production Frontier is appropriate to measure technical inefficiency among small-scale vegetable farmers over Trans-Log Stochastic Frontier.

Given the test results in Table 3, Cobb-Douglas Stochastic Production Function form observed to be appropriate to represent the production technology for surveyed small-scale vegetable producers in the study area over Trans-Log production functional form. Thus, functional form show dependent variable with several natural logarithm of inputs and household socio-economic characteristics is explained in the equation (6) and description of variables in Table 4.

$$lnYield = \beta_o + \beta_i' lnX_i' + \alpha_i' Z_i' + \mu_i \quad (6)$$

where $lnYield$ = logarithm of yield values, β_0 intercept, lnX_i' is logarithm of inputs variables, Z_i' is socio-economic variables, and β_i' and α_i' are parameter to be estimated for inputs and socio-economics variables respectively, and μ_i is the error term.

TABLE 4 Description of variable used in this analysis

Variable category	Variable name	Parameter	Variable description
Output	lnYield	N/A	Logarithm of yields-values measured in kilograms
X_Variables	lnLSize	β_1	Logarithm of land-size values measured in acre
	lnASeed	β_2	Logarithm of amount of seeds used measured in kilograms
	lnAFert	β_3	Logarithm of amount of fertilizer used measured in kilograms
	lnAChem	β_4	Logarithm of amount of chemicals used measured in liters
	lnFarmLabour	β_5	Logarithm of amount of labour force exerted measured in man-hours per season
Z_Variables	SexHead	α_1	Sex of household head; 1 = Male, 0 = Otherwise

TABLE 4 Description of variable used in this analysis (*cont.*)

Variable category	Variable name	Parameter	Variable description
	EduHead	α_2	Education obtained by household head; 1 = if obtained formal education, 0 = otherwise
	Exphead	α_3	Farming experience of household head measured in years
	Hhsize	α_4	Number of people reside in the household
	MemberFinance	α_5	Membership to micro-finance scheme for the past 1 year (1 if yes, 0 = otherwise
	Radio	α_6	Radio listening behaviour (1 if yes, 0 = otherwise)
	TotalLabour	α_7	Number of farming labour
	CostFarmLabour	α_8	Cost of farming labor in TZS
	Tomato	α_9	Crop cultivated, 1 if tomato, 0 = otherwise
	Cabbage	α_{10}	Crop cultivated, 1 if Cabbage, 0 = otherwise
	Sweetpepper	α_{11}	Crop cultivated, 1 if Sweet-pepper, 0 = otherwise
	Scarlet-eggplant	α_{12}	Crop cultivated, 1 if Bitter-tomato, 0 = otherwise
	Leafyvegetable	α_{13}	Crop cultivated, 1 if Leafy-vegetables, 0 = otherwise

5.3 *Estimation of Stochastic Frontier Model*

5.3.1 Results of Efficient and Inefficient Model

The estimated results for stochastic frontier model in Table 5 show that, the overall test of significance of all factors, Wald chi2 (18) = 1433.3, and the p-value < 0.01, meaning that production variables and socio-economic factors are reliable in predicting the vegetable production in the study area. The output elasticities of land size, amount of seeds, amount of fertilizer, amount of chemicals and labour exerted are also reported in the Table. Amount of fertilizer in the production of vegetable production among surveyed farmers

in Nzega has a huge influence in the production, as it was observed that 1% increase in amount of fertilizer has 33.7% likelihood of increasing the vegetable yields. This results is in line with other study of Everaarts et al. (2015) which found that using of fertilizer has positive effect on vegetable yields in Arusha Tanzania. Further, the 1% increase in farm-labour observed to induce 31.6% likelihood of increasing in vegetable yields, and vice versa, 1% increase in chemicals found to induce 11.5% likelihood of increasing vegetable yields, and 1% increase in land-size has likelihood of increasing vegetable yields by 9.5%. This results indicates the importance of inputs in vegetables production as vegetable is one of input demanding crop, which requires more application of improved seeds, chemicals as well as enough time of the labourers in the field (farm-labour exerted) to realize high yields (Matsumoto and Yamano, 2011; Everaarts et al., 2015; Patra et al., 2016; Schreinemachers et al., 2017).

Upon considering efficiency model (restricted model), the effect of the technical inefficiency in the variation of the output was determined using equation (6):

$$\gamma \equiv \lambda^2/[1+\lambda^2] \equiv \frac{\sigma_u^2}{\sigma_u^2+\sigma_v^2} \tag{7}$$

The estimated value of γ is 0.7093, this indicates that there are about 71% differences between the observed and the maximum frontier output among surveyed vegetable producers that explaining the inefficiencies, thus the stochastic term contributing for about 30%.

Having been assured that there is inefficiency among small-scale vegetable producers in Nzega, then analyzing the sources of the inefficiency, was among the focal objectives of this section. Upon knowing that inefficiency in agricultural production is often associated with factors related to demographic characteristics of households, farm characteristics, and the organizational and management norms of farmers themselves (Battese and Coelli, 1993; Yohannes et al., 1993; Mango et al., 2015), some socio-demographic characteristics (such as; sex of household head and education of household head); some socio-demographic characteristics were considered in the analysis (equation (6)). These characteristics include sex and education of household head; socio-economic characteristics such as household income and household size; farm characteristics such as farming experience, farming costs, farming labour, and type of vegetable crop. Since the analysis was based on technical efficiency and inefficiency models, literature suggests that the negative coefficient on the parameter estimated in the inefficient model indicates a decrease in inefficiency, and vise-versa (Abdulai et al., 2011; Mango et al., 2015; Ahmadzai, 2017).

Results in Table 5 indicate that technical efficiency in vegetable production in Nzega is significantly influenced by farm-experience, household size, radio-listening behaviour, number of farm workers, cost of farm labour, and type of vegetable crop cultivated.

TABLE 5 Maximum likelihood estimation of stochastic frontier model and inefficiency model

Independent variables	Parameter	Coef.	Std. err.	z	P > z
Dependent variable: Ln of crop yield (in kg)					
Stochastic Production Frontier Model					
Constant	β_0	1.502	0.52	2.88	0.0040***
Ln land size (in acres)	β_1	0.095	0.04	2.14	0.0330**
Ln amount of seeds (in grams)	β_2	0.032	0.02	1.62	0.1060
Ln amount of fertilizer (in kg)	β_3	0.337	0.03	12.90	0.0000***
Ln amount of chemicals (in liters)	β_4	0.115	0.01	11.51	0.0000***
Ln farm-labour force (in hours)	β_5	0.316	0.06	4.92	0.0000***
Technical Inefficiency Model					
Constant	α_0	0.268	0.03		
Sex (1 = male, 0 = female)	α_1	0.064	0.05	1.30	0.1950
Education (1 = formal school, 0 = no formal school)	α_2	0.044	0.05	0.94	0.3460
Farming experience (in years)	α_3	−0.003	0.00	−2.19	0.0290**
Household size	α_4	0.066	0.01	6.52	0.0000***
Total no. of farm-labour	α_7	−0.072	0.02	−4.61	0.0000***
Member in Microfinance Scheme (1 if yes, 0 if no)	α_5	0.037	0.04	1.04	0.3010
Cost of farm-labour	α_8	0.000	0.00	3.69	0.0000***
Radio listening behaviour (1 if yes, 0 if no)	α_6	−0.105	0.03	−3.04	0.0020***
Tomato (1 if cultivated, 0 if not)	α_9	0.009	0.05	0.17	0.8620
Cabbage (1 if cultivated, 0 if not)	α_{10}	0.130	0.07	1.93	0.0540*
Sweet-pepper (1 if cultivated, 0 if not)	α_{11}	0.032	0.05	0.63	0.5260
Scarlet-eggplant (1 if cultivated, 0 if not)	α_{12}	0.371	0.06	6.55	0.0000***
Leafy-vegetables (1 if cultivated, 0 if not)	α_{13}	−0.072	0.04	−1.63	0.1040

TABLE 5 Maximum likelihood estimation of stochastic frontier model (*cont.*)

Independent variables	Parameter	Coef.	Std. err.	z	P > z
Sigma_v		0.279	0.02		
Sigma_u		0.436	0.05		
Lamda		0.268	0.03		
Sigma2		1.562	0.07		
Number of Observation		528			
Wald chi2(18)		1433.3			
Prob > chi2		0.000			
Log likelihood		−237.52828			

* , ** and *** represent significance at 10% , 5% and 1% levels, respectively

5.3.2 Technical Efficiency Distribution

To obtain the technical scores, the econometric estimations of equation 6 were used to predict technical efficiency scores (TE). It was observed that technical efficiency scores (TE) of vegetable producers in the study area ranged from 20.6% to 94.0% with a mean technical efficiency of 73.1% and a standard deviation of 11.6%. This means that from the overall total performance (total sample), on average, the vegetable producers in the study area were 26.9% below the production frontier. This can further suggest that there was a possibility of these producers to increase their productivity by improving their efficiency while using the same type of inputs (Table 6).

The descriptive results are slightly different when considering adopters and non-adopters of CDT, separately, because for adopters mean TE is 75.4%, while for non-adopters, mean TE is 71.6%. In addition, some non-adopters require more improvement to attain efficient level compared to adopters, as their minimum TE starts from 20.6%, about 29.3% lower than their counterpart

TABLE 6 Summary statistics of Technical Efficiency score (TE)

Usecdt	Obs	Mean	Median	Std Dev	Skewness	Kurtosis	Min	Max
Non-adopter	308	0.7155	0.7445	0.1333	−1.0275	3.8463	0.2060	0.9307
Adopter	220	0.7541	0.7630	0.0803	−0.6409	3.4804	0.4988	0.9400
Total	528	0.7315	0.7551	0.1159	−1.2065	4.8425	0.2060	0.9400

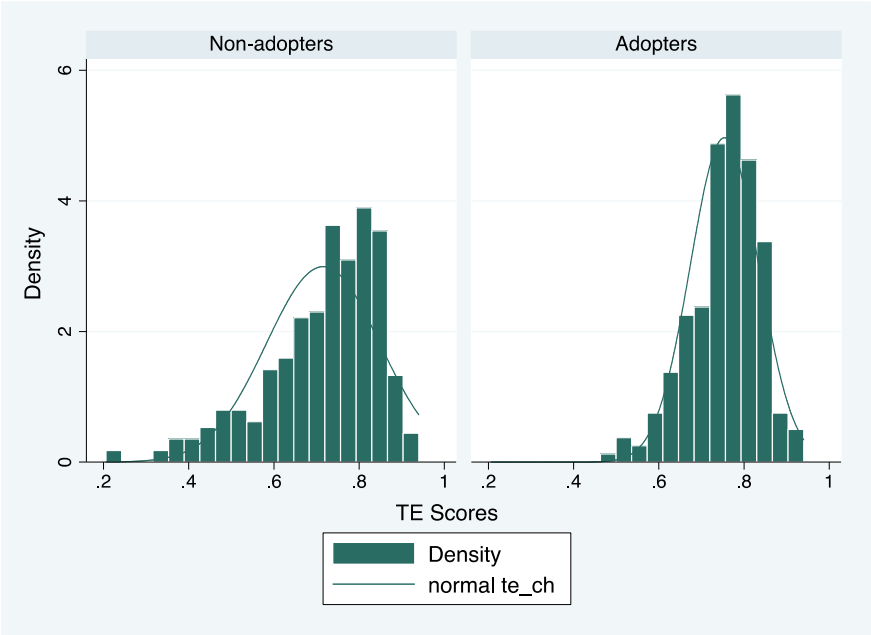

FIGURE 1 Technical efficiency distribution

adopters. It is also observed that both adopters and non-adopter of CDT have median technical efficiency scores higher than their means, at 76.3% and 74.5%, respectively. This means that both adopters and non-adopters of CDT are negatively skewed, which indicates existence of inefficiency in the production function (Kumbhakar et al., 2015). However, since the difference between mean and median technical efficiency scores for both adopters and non-adopters of CDT is 0.04 and 0.02, respectively, there is nearly similar distribution of technical efficiency scores among adopters and non-adopters of CDT except for a few outliers, as it is illustrated in Fig. 1.

5.4 *Effect of Adoption on Technical Efficiency and Crop Yield*

To obtain the actual effects of adoption of CDT on technical efficiencies and yields, the PSM method was used to evaluate the average treatment on the treated (ATT). The most common matching algorithms were employed to measure the effect using Nearest Neighbour Matching (NNM) and Kernel Matching Method.

5.4.1 Matching Results

Table 7 shows the NNM and KMM results for comparison of adopters and non-adopters of CDT. For NNM, 220 adopters of CDT were matched with 67

TABLE 7 Average Treatment effects on the Treated (ATT) using NNM

Method	Outcome	ATT	Std error	t-value	No. of treated	No. of control
NNM	Technical Efficiency	0.029***	0.068	0.420	220	67
	Crop Yield	427.117***	480.216	0.889	220	67
KMM	Technical Efficiency	0.030***	0.021	1.379	220	308
	Crop Yield	455.435***	202.328	2.251	220	308

***Significant at 1% level

non-adopters. The results indicate that the adoption of CDT is positive and significant at 1% level; again, results show that adoption of CDT can result up to 2.9% increase in technical efficiency, and up to 427.12 gg of vegetable yields per season (12 months). The results for KMM are the same as for NMM (in terms of sign and significance), but slightly improved in the magnitude, as the adoption of CDT can lead up to the 30% increase in technical efficiency with up-to 455.44 kg increase in vegetable yields per season (12 months).

6 Discussion

Technology use has a direct impact on the productivity and so does to yield. As explained in the beginning, productivity enriched by changing of combination of inputs, failure of farmers to use the proper combination resulted into inefficiencies in production. Socio-demographic, socio-economic, farm level as well farmers' associations have been claimed to play a vital role to either encourage or discourage production efficiencies. In this study it was found that, farm-experience, household size, radio-listening behaviour, number of farm workers, cost of farm labour, and type of vegetable crop cultivated influencing production efficiencies.

The question whether farming experience is improving or discouraging adoption of technology and in so doing improves or discourages yield, is unclear (Ainembabazi and Mugisha, 2014). Some sources believed that long farming experience also reflects the old age of farmers, which does not favour adoption of technology, and so negatively affects yields (Martey et al., 2013), Other sources claim that farmers can accumulate crop production experience and progressively switch from traditional to improved technologies, and

eventually are able to realize high yields (Dosi, 1982; Feder et al., 1985). The reported findings in Table 6 are in line with the latter case, as farming experience was found to be associated with decreasing likelihood of production inefficiency (i.e., increasing production efficiency). The fact that mean farming experience of vegetable producers is 24.30 years, while the minimum and maximum farming experiences are 3 and 66 years (with standard deviation of 11.5 years), respectively (as indicated in Table 2), this confirms that the majority of farmers have enough farming experience that enables them to be rational in adopting various agricultural technologies and eventually realizing high yields.

Basically, small-scale agriculture in the developing world, including Tanzania, is pre- dominantly labour-intensive; hence, farm labour is an important factor that facilitates agricultural production processes in these areas (Huong et al., 2013; Everaarts et al., 2015). The source of farm labour can be the family or can be hired, thus farming households with substantial amount of farm labour are more likely to adopt various technologies and eventually realize high yields (Kansiime et al., 2014). Results in Table 5 are in line with this observation, as total number of farm workers were negatively influencing the likelihood of production inefficiency (i.e., increasing production efficiency). One percent increase in farm labour can increase production efficiency by 7.2%. However, having more or substantial amount of household size cannot guarantee source of farm labour from the respective household. Most of the time, the composition of the individuals in the respective households matters, as those farming households with more dependants (household members with below 15 or above 65 years) can run short of family-labour and affect the likelihood of production efficiency (Audu and Aye, 2014). This situation normally forces such households to use more of hired farm labour which also increases cost of farm labour, and in-turn discourages the efforts to increase output. It has also been observed in this study that both household size and cost of farm labour increase the likelihood of production inefficiency (i.e., reduce production efficiency); although for cost of labour, the magnitude is very insignificant (4.3e–05%) compared to household size which is 6.3%.

Knowledge and awareness of agricultural activities have been regarded as fundamental factors in the agricultural production processes. The results from the current study suggest that farmers in Nzega, with radio-listening behaviour were found to reduce the likelihood of production inefficiency (i.e., increasing production efficiency) for about 10%. The results are consistent with previous studies which have shown that radio broadcast, especially agricultural-based programs have been mostly used to inform as well as educate rural dwellers on various crop production information (Al-Hassan et al., 2011; Johnson and Rajadurai, 2015; Mtega, 2018). Farmers with radio-listening behaviour seem to be more knowledgeable and proactive to adopt certain agricultural

technologies; they are also able to realize production potentials efficiently, contrary to those who do not have the radio-listening behaviour (Alia et al., 2013; Manda and Wozniak, 2015).

Furthermore, literature suggest that, the type of crop under multiple crops production in a single farm (i.e., diversification), has influence on production inefficiency (Ahmadzai, 2017). This has also been observed in this study, as small-scale cabbage producers were noted to reduce inefficiency while scarlet-eggplant producers were observed to increase the inefficiency (Table 5). Given the fact that there are differences in agronomic requirements for various vegetables, farmers do vary their input levels given their knowledge on production, local experience, soil structure and weather conditions, which happened to be either too much, optimal or low. Application of these inputs influences production inefficiency (Wassie, 2014; Srinivasulu et al., 2015; Abdoulah Mamary et al., 2018; Ngango and Kim, 2019). This has also been observed in the study area, in which cultivating of cabbage can significantly (at 5%) reduce production inefficient by 17%, while cultivating scarlet-eggplant can significantly (at 1% level) increase inefficiency by 38%.

In addition, production efficiencies of those vegetable farmers who used CDT were higher compared to those who did not use CDT. This means that, these adopters of CDT were able to produce more outputs using the same input levels (i.e., fertilizer, chemicals, seeds and labour) as compared to their counterpart non-users of CDT. Using of CDT assures the availability of water for vegetable production. Thus, this findings indicating the importance of water in enhancing investment in agriculture, particularly to horticultural crops (Jha et al., 2019; Sidibé, 2005).

7 Conclusion

These findings are important particularly in informing farmers in Tanzania and agricultural stakeholders in general that when encouraging farmers to increase the use of agricultural inputs, strategies to enhance use of the inputs should be taken with precaution given the variation of status of farmer households. Given that agriculture is highly dependent on water availability, water for irrigation has a huge influence on agricultural production. The presumption is that having an assurance of water for irrigation, a rational farmer can invest more in particular crop production, including investment in inputs use hence become efficiently in production. The same applied for the study area, whereby assurance of water to irrigate the vegetables made the adopters of CDT employ more inputs (inorganic fertilizer and chemicals) than their counterpart non-adopters; hence, the former realized a higher yield than the latter.

This was also supported by extension officers in the respective wards and villages, who were of the opinion that once an individual farmer has assurance of irrigation water, he or she tends to spend much on agro-inputs, leading to high crop yields. However, use of optimal agro-inputs has to be observed, otherwise poor inputs will lead to low productivity. Thus, the presence of extension officers to guide the farmers on the proper use of water and other inputs is very crucial.

As it has been observed, having too many people at a given household does not guarantee adequate farm labour, which is necessary in labour-intensive agriculture. Increasing the cost of inputs, for instance labour costs, cannot guarantee increase in output, especially for non-constant return to scale production functions. Meanwhile, not every vegetable crop can give the desired outputs. Results from the analysis present the essential intuitions about adoption of CDT and its effects on production efficiencies. Generally, it was observed that there was inefficient use of inputs (land-size, labour, quantity of improved seeds, amount of chemical used and amount of fertilizer used) among small-scale vegetable producers. The inefficiency was basically observed to be caused by household-size, cost of farm labour as well as growing cabbages and scarlet-eggplants. It is further observed that, farming experience, number of farm workers and radio listening behaviour reduced technical inefficiency (i.e., improve technical efficiency). In addition, when conducting further analysis using PSM methods, it was found that the adoption of CDT among vegetable producers in the study area significantly increased the efficient use of inputs and hence improved crop yields.

Therefore, the findings of this study would suggest, that technologies like CDT should be encouraged, especially to small-scale farmers in arid and semi-arid areas. Furthermore, experienced farmers should share expertise on the use of inputs, with other less experienced farmers. In line with this, the role of agricultural information and extension officers on improvement of production efficiency should not be undermined in improving efficient use of inputs. Hence, programmes and intervention that focus on encouraging farmers to listen to radio programmes related to agriculture, particularly those covering specific crop and location, are recommended.

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