MPRA
Munich Personal RePEc Archive

Efficiency and productivity analysis of vegetable farming within root and tuber-based systems in the humid tropics of Cameroon

Akamin, Ajapnwa and Bidogeza, Jean-Claude and Minkoua N, Jules René and Afari-Sefa, Victor

Faculty of Economics and Management, University of Yaounde II, Soa P.O. Box 18, Cameroon, Liaison Office Cameroon, West and Central Africa, World Vegetable Center, Messa P.O. Box 2008, Cameroon, Faculty of Economics and Management, University of Yaounde II, Soa P.O. Box 18, Cameroon, Samanko Research Station, West and Central Africa, World Vegetable Center, Bamako P.O. Box 320, Mali

2017

Online at https://mpra.ub.uni-muenchen.de/85329/

MPRA Paper No. 85329, posted 29 Jan 2019 16:14 UTC

Efficiency and productivity analysis of vegetable farming within root and tuber-based systems in the humid tropics of Cameroon[1]

Ajapnwa Akamin[1], Jean-Claude Bidogeza[2], Jules René Minkoua N[1], Victor Afari-Sefa[3]

[1] Faculty of Economics and Management, University of Yaounde II, Soa P.O. Box 18, Cameroon
[2] Liaison Office Cameroon, West and Central Africa, World Vegetable Center, Messa P.O. Box 2008, Yaoundé, Cameroon
[3] Samanko Research Station, West and Central Africa, World Vegetable Center, Bamako BP 320, Mali

Abstract

The study analyzes the technical efficiency of vegetable farmers in root and tuber-based farming systems within selected sites of the humid tropics of Cameroon. Multistage sampling was used to collect primary data from a cross-section of vegetable farmers drawn from eight selected sites in Santa sub division, Northwest region of Cameroon. Stochastic frontier analysis was used to estimate the technical efficiency of vegetable farmers and to examine its determinants. The results showed that farmyard manure was the most productive factor input, followed by farm equipment and labor. The mean technical efficiency level was 67%, revealing production shortfalls and indicating possibilities of significantly increasing production with the current input levels. Female, as well as more educated farmers were found to be significantly more efficient than their counterparts. The results also showed that farmers become less technical efficient as farm sizes become larger. Our study findings suggest that smallholder farmers' access to manure, farm implements, and increased women participation in vegetable farming, will produce huge payoffs in vegetable production efficiency in Cameroon.

Keywords: technical efficiency, vegetable productivity, farming systems intensification, crop diversification, stochastic frontier analysis

JEL Classification: D24, Q12, C21

---

[1] The final version of this paper is published as follows:
Akamin, A., Bidogeza, J.-C., Minkoua, J. R., & Afari-Sefa, V. (2017). Efficiency and Productivity Analysis of Vegetable Farming within Root and Tuber-Based Systems in the Humid Tropics of Cameroon, *Journal of Integrative Agriculture*, 16(8), 1865-1873, **https://doi.org/10.1016/S2095-3119(17)61662-9**

Correspondence address: Ajapnwa Akamin, email: akaminajap@gmail.com ; Jean-Claude Bidogeza, email : bidogeza@yahoo.fr , jeanclaude.bidogeza@worldveg.org

1. Introduction

The role of agriculture in building the economy of many countries in sub-Saharan Africa (SSA) is well known. The agriculture sector employs the major work force and contributes significantly to the Gross Domestic Product (GDP) in these SSA economies (AGRA 2015). Agriculture is still regarded as the backbone of most economies and draws significant attention from governments and development agencies as it is the main source of employment and livelihood for the major population, particularly the most vulnerable. In Cameroon, the total agricultural production turnover in terms of value including food production has been on the rise, notably between 1997 and 2012. Agricultural production rose from USD 2.6 billion in 1997 to USD 3 billion in 2002, to USD 4.3 billion in 2007, and to USD 5.6 billion USD in 2012 (FAO 2015). The major crops in terms of production volume include cassava (*Manihot esculenta*), plantain (*Musa paradisiaca*), maize (*Zea mays*), taro (*Colocasia esculenta*), banana (*Musa acuminata* and *Musa balbisiana*), sugar cane (*Saccharum officinarum*), sorghum (*Sorghum bicolor*), fresh vegetables, cocoa (*Theobroma cacao*) and coffee (FAO 2015). Despite the steady increase in food crop production, the country is still experiencing food deficit and severe malnutrition. Food inflation was estimated at 1.71% in 2014, while the economic cost of malnutrition incurred per annum is estimated at USD 0.6 billion for Cameroon (UNICEF 2013). In addition, there has been a gradual decline in the agricultural sector contribution to total GDP. The agricultural sector input to GDP in 2014 for instance was only 16.9%, though it holds more than 42% of the total labor force (Doffonsou and Singh 2014).

Vegetables are an important source of micronutrients for human nutrition. When taken in sufficient quantities, vegetables help to prevent cardiovascular diseases such as diabetes and cancer (FAO 2013; Uusiku *et al*. 2010; Yang and Keding 2009). Given the nutritional importance of vegetables, the World Health Organization (WHO) and the Food and Agriculture Organization (FAO) recommend the consumption of fruits and vegetables at least 400 grams per capita per day (excluding starchy root crops) to avoid micronutrient deficiencies, heart and cancer related diseases (FAO 2014). In Cameroon, like many other SSA countries, vegetables are poorly consumed in terms of quantities. Kagma *et al*. (2013) have estimated that on the average, only 46 grams of vegetables per capita per day in Cameroon. This represents only 11.5% of the FAO/WHO recommended intake.

Generally, cropping enterprise interest in the humid tropics of Cameroon has mainly focused on the potential of technologically intensive root and tuber crops, other staple food crops, timber, non-timber forest products, coffee and cocoa (Nchare 2007; Binam *et al*. 2008). Traditional and exotic vegetables have received little research and development attention in SSA in terms of their contributions to reducing malnutrition and poverty, and by extension for improving national economic growth (Drechsel and Keraita 2014; FAO 2014; Shackleton *et al*. 2009). Some efforts though are being recorded owing to synergy between local government institutions, and regional and international agricultural research centers such as the World Vegetable Center and the Consultative Group on International Agricultural Research centers (for instance the Humidtropics program and the Traditional African Vegetables project).

Smallholder vegetable farming in the humid tropics of Cameroon is one of the major drivers for change towards sustainable agricultural production with optimal efficiency. Inefficiency in farming at the smallholder level has been identified as one of the major constraints hampering the effective development of the agricultural sector (Dewbre and Borot de Battisti 2008). In Kenya's drylands, inefficiency in the use of scarce farm production resources has resulted in low farm productivity (Lemba et al. 2012). Haji (2006) equally noted that technical, allocative and economic inefficiencies cause efficiency differentials among vegetable farmers in vegetable-dominated mixed farming systems of eastern Ethiopia. Hence, there is need for an accurate assessment of the technical efficiency of vegetable farming and subsequent identification of the sources of technical inefficiencies thereof in order to suggest possible policy options and scenarios to optimize farm production. To this end, this study aims to estimate the technical efficiency of vegetables farmers within root and tuber-based cropping systems, identify sources of technical inefficiency, and investigate the relationship existing between technical efficiency and socio-economic variables that characterize vegetables farmers. We hypothesize that all the vegetable farmers under consideration are equally and fully technically efficient, and that there is no significant relationship between their technical efficiency levels and factors assumed to influence them. The remainder of this paper is structured as follows: section 2 describes the material and methods used for the study, section 3 presents the results of the study, while section 4 highlights the conclusions and policy implications of the study.

2. Materials and Methods

2.1 Modeling framework

Various approaches have been used to empirically measure technical efficiency and these techniques can be classified based on whether they impose a functional form on the underlying production function or not (i.e. parametric versus nonparametric). The two most popular techniques used in the literature are Data Envelopment Analysis (nonparametric) and Stochastic Frontier Analysis (parametric). The DEA technique first introduced by Farell (1957) and further developed by Charnes *et al.* (1978) employs a nonparametric approach to estimate technical efficiency. However, the main criticism of this technique as underscored in the literature is that it ignores the effect of stochastic error and ascribes all deviation from the frontier to inefficiency (Kopp and Smith 1980; Thiam *et al.* 2001; Murillo-Zamorano 2004). Moreover, the non-inclusion of a disturbance term makes it difficult to perform statistical tests. The Stochastic Frontier Analysis (SFA) technique is usually preferred in the agricultural economics literature because unlike DEA which attributes shortfalls to inefficiency, SFA allows for distinguishing between deviation from the frontier that is due to inefficiency and that which is due to measurement error and exogenous shocks (Coelli, 1995).

Given the agricultural context of this study where most small-scale farmers seldom keep records of farm transactions and where farm yields are vulnerable with respect to erratic weather, pest attacks and other external factors, attributing all deviation to inefficiency would indeed be a very strong assumption and might bias our estimates. Thus, we use SFA to estimate technical efficiency in this paper.

Measurement of technical efficiency: stochastic frontier analysis

Aigner *et al*. (1977) and Meeusen and van den Broeck (1977) introduced the stochastic production frontier model that is typically written as:

$$y_i = f(x_i;\beta)e^{\varepsilon_i} \tag{1}$$

$$\varepsilon_i = v_i - u_i \tag{2}$$

$$v_i : N(0,\sigma^2_v) \tag{3}$$

$$u_i : F \tag{4}$$

Where y is a scalar of observed output of the i-th producer, x is a vector of inputs and $f(x_i;\beta)$ is the deterministic kernel (production frontier in this case). The composed error term ε_i has two components: (i) a symmetric disturbance (v) that captures exogenous shocks and measurement error, and (ii) a non-negative technical inefficiency component u. The error term components (u and v) are assumed to be independent of each other, of the regressors and identically distributed across all observations[2].

We assume a Cobb-Douglas technology for the production function since the interpretation of its coefficients is straightforward. Although, a likelihood ratio (LR) test can be used to determine the appropriate functional form, the choice of functional form is of trivial importance in the measurement of efficiency (Kopp and Smith 1980).

Based on our cross-sectional framework, the linearized Cobb-Douglas stochastic production frontier model is written as follows:

$$\ln y_i = \ln A + \sum_{k=1}^{n} \beta_{ki} \ln x_{ki} + v_i - u_i \tag{5}$$

Estimation method

The Maximum Likelihood technique is used to estimate equation (5) because unlike other estimation methods (mostly distribution-free techniques), it enables us to distinguish inefficiency from statistical error. A proviso to applying this technique is that we assume a particular distribution for the inefficiency component (u). Possible distributions include the Half-Normal of Aigner *et al.* (1977) $u : N^+\left(0, \sigma_u^2\right)$, the Exponential distribution of Meeusen and van den Broeck (1977), the Truncated-Normal $u : N^+\left(\mu, \sigma_u^2\right)$ and the Gamma distribution. A likelihood ratio (LR) test is used in this study to choose between the half-normal and the truncated-normal distribution.

Given the independence assumption between *u* and *v,* we use the λ parameterization of Aigner *et al.* (1977) and thus write the log-likelihood function for the Normal-Truncated Normal model à la Kumbhakar and Lovell (2000):

$$\ln L = \text{constant} - H \ln \sigma - H \ln \phi\left(\frac{\mu}{\sigma_u}\right) + \sum \ln \Phi\left(\frac{\mu}{\sigma\lambda} - \frac{\varepsilon_i \lambda}{\sigma}\right) - \frac{1}{2}\sum\left(\frac{\varepsilon_i + \mu}{\sigma}\right)^2 \tag{6}$$

Where $\sigma = \left(\sigma_u^2 + \sigma_v^2\right)^{1/2}$, $\lambda = \sigma_u / \sigma_v$ and $\sigma_u = \lambda\sigma \big/ \sqrt{1+\lambda^2}$ are variance parameters, while

[2] The assumption that *u* is independent of the regressors is later relaxed in order to be able to identify sources of inefficiency.

$\Phi[.]$ denotes the standard normal cumulative distribution function. Lambda takes any non-negative value; as lambda approaches zero, σ_u tends to zero and/or σ_v tends to infinity. This means the deviation from the frontier is increasingly being accounted for by the idiosyncratic disturbance term. When lambda instead tends to infinity, then inefficiency outweighs stochastic error in the composed error term and the model gradually reduces to a deterministic frontier function. The maximization of the log-likelihood function gives estimates of the model coefficients and variance parameters.

After estimating the model parameters, we use the mean of the conditional distribution of u on ε $\left[f(u\,|\,\varepsilon) = f(u,\varepsilon)/f(\varepsilon)\right]$ to obtain point estimates of technical inefficiency, following Jondrow *et al.* (1982). The technical efficiency index for each producer is then computed using the estimator of Battese and Coelli (1988) because it is more consistent with the definition of technical efficiency (Kumbhakar and Lovell 2000).

$$\text{Technical efficiency} = E\left[\exp(-\hat{u}_i)\,|\,\varepsilon\right] \tag{7}$$

The second objective of this study is to identify the sources of technical inefficiency (inefficiency effects). Inefficiency effects have been empirically investigated using either the one-step or the two-step procedure. In the two-step approach, the observation-specific (in)efficiency index is first estimated and subsequently regressed on a vector of variables that are believed to influence efficiency in a second estimation (see Pitt and Lee 1981; Kalirajan 1981). This two-step procedure has been castigated on the grounds that the error components which are assumed to be independently and identically distributed in the first step are however assumed to be a function of certain producer-specific factors in the second step (Coelli 1995).

The one-step procedure circumvents the aforementioned limitation and incorporates heteroscedasticity by estimating the parameters of the factors which are said to influence inefficiency simultaneously with those of the stochastic frontier function in a single estimation. To do this, we parameterize one or all of the distribution parameters (i.e. μ and/or σ_{ui}^2) in terms of some underlying exogenous variables (Kumbkakar and Wang 2010). Hence, in this paper we adopted the one-step approach following the study of Caudill and Ford (1993). As a result, we parameterize the variance of the inefficiency distribution as follows:

$$\sigma_{ui}^{2} = \exp(z_i'\delta) \tag{8}$$

Where σ_{ui}^{2} is the technical inefficiency variance; z_i is a vector of explanatory variables and δ is a vector of unknown parameters (inefficiency effects).

Empirical model specification

The empirical stochastic frontier production function model for the *i*-th farmer is specified in this study within a cross-sectional framework as follows:

$$\ln y_i = \beta_0 + \beta_1 \ln land + \beta_2 \ln labour + \beta_3 \ln manure + \beta_4 \ln ferti + \beta_5 \ln seed + \beta_6 \ln chem + \beta_7 \ln equip + v_i - u_i \tag{9}$$

Where $\ln y_i$ denotes the total value (in CFA francs) of vegetables produced (in natural log). $\ln land$ is the natural log of total area used for vegetable production (in square meters); $\ln labour$ represents the natural log of labor used (measured in man-days); $\ln manure$ represents the natural log of all manure used (in bags); $\ln ferti$ represents the natural log of the total cost of fertilizer used (in CFA francs); $\ln seed$ represents the natural log of total cost of all vegetable seeds (in CFA francs); $\ln chem$ represents the natural log of total cost of chemicals (in CFA francs); and $\ln equip$ represents the natural log of total cost of equipment used (in FCFA francs).

The explanatory variables used in the production function are amongst those that have been identified as critical to smallholder vegetable farming in sub-Saharan Africa (Shackleton *et al.* 2009; Drechsel *et al*. 2014; Rejandran *et al*. 2015). The production period in this study commences from the last rainy season through to the dry season prior to the field survey. Most vegetable farmers typically produced more than one type of vegetable in a particular season. The quantity of each vegetable produced is thus multiplied by its selling price to obtain its overall value. The values of the individual vegetables are then summed up to obtain the aggregate output, y. Most studies that have focused on farm (rather than on specific-produce) efficiency have considered the monetary value of output instead of the physical quantities (for instance Coelli and Battese 1996; Bravo-Ureta and Pinheiro 1997; Rejandran *et al*. 2015). Input quantities relate only to what was utilized for vegetable production. Labor includes family labor, hired labor, as well as labor offered gratis by other persons and are all assumed to be equally efficient. Farmyard manure comprises mostly poultry droppings packed in bags in dry form or fresh domestic poultry litter. Fertilizer includes both NPK and urea. Chemicals inputs (expressed in monetary terms) include insecticides, herbicides and fungicides utilized during the production period. Equipment refers to the sum of annual depreciation for each farm implements (machetes, water pumps, rubber boots, etc.) and other assets dedicated to farm use; that is, the amount of each tool/implement that was utilized during the reference production period.

The inefficiency effects model used to examine the effects of exogenous factors on the technical (in) efficiency of vegetable farmers is specified as follows:

$$\sigma_{ui}^2 = \exp\left(\delta_0 + \delta_1 z_{age} + \delta_2 z_{sex} + \delta_3 z_{ownership} + \delta_4 z_{educ} + \delta_5 z_{area} + \delta_6 z_{location} + \delta_7 z_{credit} + \delta_8 D_{divers2} + \delta_9 D_{divers3} + \delta_{10} z_{extension}\right) \quad (10)$$

Where σ_{ui}^2 is the variance of technical inefficiency; the *δ's* denote inefficiency effects; z_{age} is the age of the vegetable farmer (in years); z_{sex} is the gender dummy of the vegetable farmer (male=1, otherwise=0); $z_{ownership}$ is a dummy capturing farm ownership (=1, if owns farms; =0, otherwise); z_{educ} is a dummy representing the farmer's maximum level of formal schooling (at least secondary=1; =0, otherwise); z_{area} is the size of the vegetable farm (in meters squared); $z_{location}$ is the farm location dummy (PINYIN=1; =0, otherwise). In this study, the term PINYIN groups together 5 out of the 8 sites where the data was collected (Pinyin, Menka, Buchi, Meforbe, Mbei). The study sites that are grouped in two categories (PINYIN sites and others) are differentiated based on their relief and soil characteristics; intermediate relief, aliatic and penevoluted ferralitic red soils for PINYIN as opposed to penevoluted ferralitic soils and low altitude for the rest of the sites. z_{credit} is a dummy capturing the influence of credit constraints on technical efficiency (access=1; =0, otherwise); the influence of crop diversification on technical efficiency is captured by considering the cultivation of single vegetable species (1), the cultivation of two or more vegetable species (2) and the cultivation of at least one vegetable species together with roots/tubers (3). We therefore have three dummies for our model: $D_{divers1}$ (=1, if farmer cultivates only single vegetable type; =0, otherwise), $D_{divers2}$ (=1, if farmer cultivates at least two vegetable types but with no other crop; =0, otherwise) and $D_{divers3}$ (=1, if farmer cultivates at least one vegetable type together with root/tuber crops; =0, otherwise), where $D_{divers1}$ is our reference category. $z_{extension}$ is the extension contact dummy (yes=1; =0, otherwise).

2.2 Data

Multistage sampling was used to collect primary data for the 2014/2015 farming season. First, Santa sub division was purposely chosen for the survey because it is dominated by both roots/tubers and vegetables. Following discussions with farmers and baseline information obtained from the Santa Council, eight villages which make up the main vegetable-producing sites were then identified, where a structured questionnaire was administered. Pre-testing was done and most of the questionnaires were administered in English and lingua franca (*pidgin* English) for easy understanding. Farmers were chosen at random and the number of farmers chosen from each site was determined as a function of the latter's population. A total of 71 questionnaires were retained for the 8 villages after discarding those with unreliable data: Lower Pinyin (n=9), Menka (n=10), Buchi (n=10), Meforbe (n=10), Santa (n=8), Mbei (n=10), Njong (n=8), and Baligham (n=6). Farmers were randomly chosen.

Data was collected for the last rainy and dry season prior to the survey and relates to household characteristics, land, production and other relevant information. Precisely, demographic information concerns the farmer's age, sex, educational attainment, experience and main economic activity. Land information includes total area used for vegetable cultivation during the previous farming period, mode of land acquisition, cropping system and main vegetables cultivated. Data was also collected on the various quantities and prices of inputs used, as well as the prices and quantities of the different vegetables cultivated during the period in question. These vegetables include leek, parsley, African nightshade, cabbage, pepper, tomato, onion, celery, lettuce, carrot, beetroot and other vegetables. Relevant information on access to credit, contact with extension agents as well as major problems faced was also collected. Supplementary secondary data was obtained from local administrative units, research centers, NGOs, and online repositories.

3. Results

3.1 Descriptive statistics

Input-output data and characteristics of the vegetable farmers are contained in Appendix A1 and A2 respectively. The average farmer realized at least 2 million francs (US$3,636) from vegetable cultivation in the last farming season. In terms of inputs, the average farm size is less than 0.6 ha. Apart from cabbage and African nightshade, vegetables are generally cultivated on smaller plots (as small as 300 m²) since they only serve as supplements to staple foods like corn, taro, cassava and potato. On the average, farmers spent about 131 man-days on their vegetable farms (0.53 ha on average). There is high dependence on organic manure and chemical fertilizer due to poor soil content. Each farmer uses on average 77 bags of approximately 50 kg each of manure, and spends close to 156,000 CFA Francs (US$ 283) on inorganic fertilizers (Urea and NPK). In terms of equipment, 55 % of the farmers (39) owned water pumps, 86 % (61) owned water cans and 93 % owned chemical sprayers. Each farmer used approximately 37,000 CFA Francs (US$67) worth of equipment during the farming period under consideration. The average age of respondents was 38 years with most of them being men (83%) since they have more access to land. Moreover, women cultivate more of staple food crops. About 57% of growers do not own land and almost all of them intercrop vegetables and other root and tubers or cereal crops. About 44 % had access to loans from friends, local associations, credit unions and banks.

A series of tests were performed to validate the application of SFA and to choose a distribution for the inefficiency term. The first test which verifies whether it is worthwhile specifying the model as stochastic is based on the skewness of the Ordinary Least Squares residuals. The test statistic of -0.135 indicates negative skewness and thus justifies the stochastic specification of the frontier model. A likelihood ratio (LR) test was performed to choose between the half-normal and the truncated-normal distribution (i.e. H_0: μ=0). Its LR statistic of 19.5 exceeds the 1 % critical value of 5.4 (at one degree of freedom). Hence, the half-normal distribution is strongly rejected in favor of the truncated-normal. The presence of technical inefficiency was also verified using the LR statistic[3]. The test statistic which has a value of 19.5 exceeds the critical value of 17.9 at 10 % significance level (with 12 degrees of freedom). Hence, we reject the assumption of no technical inefficiency. The test results are summarized in Appendix A3.

3.2 Productive factors in vegetable farming

After confirming the presence of technical inefficiency, the truncated-normal stochastic frontier and the inefficiency effects models were estimated using Maximum Likelihood following the one-stage procedure. Table 1 presents the stochastic frontier estimates. The estimated coefficients in Table 1 are interpreted as output elasticities given that a Cobb-Douglas technology was assumed. Most of the estimated coefficients have the expected signs.

[3] The statistic used for the LR tests is given as $LR = -2\ln\left[L(H_0) - L(H_1)\right]$, where $L(H_0)$ and $L(H_1)$ are the log-likelihood values of the restricted model (with the null hypothesis) and unrestricted model (with the alternative hypothesis) in each case. The LR tests are verified from a mixed chi-squared distribution (table of Kodde and Palm 1986).

Apart from seeds and chemicals, all other inputs significantly influence vegetable production, (manure and equipment at 5%, land and fertilizer at 1 % and labor at 10 % significance levels).

The output elasticities show that manure is the most productive factor of production, with the capacity to increase output by 46.3 % if the quantity of farmyard manure is increased by 100 %. The importance of farmyard manure cannot be overemphasized given the relatively poor soils in Santa sub Division. Manure is used intensively given that it is more affordable compared to fertilizer. The next productive factor inputs in order of importance are farm equipment/tools, followed by land and labor. Each of these three inputs explained vegetable production increase by 30, 27, and 26 %, respectively following a doubling of applied quantities. The highly significant effect of equipment/tools can be explained by the fact that it is one of the key limiting factors in vegetable cultivation. Water pumps and water cans for instance play a determining role during the dry season and in areas with limited water supplies. Their availability therefore increases production. The results show that fertilizers do not boost vegetable production, unlike manure. This however contradicts a priori expectation given that fertilizer should improve production, ceteris paribus. A possible explanation could be that farmers either do not respect the recommended rate of fertilizer application per vegetable species per farm size, or they use fertilizer of doubtful quality. Empirical studies (Liverpool-Tasie *et al.* 2010; Khor and Zeller 2014) have reported cases where the labeled content of a fertilizer pack does not reflect its true composition. Moreover, smallholders are usually more vulnerable to fertilizer of doubtful quality as they do not have the means to conduct proper inspection to check the quality of the fertilizers.

[Table 1 here]

The returns to scale, measured via the total elasticity of production, is obtained by summing the output elasticities for all the inputs. When all inputs are simultaneously doubled, vegetable production increases by 115 percent. This implies that there is increasing returns to scale. The lambda statistic which measures the ratio of inefficiency to measurement error variability is estimated at 1.78. This indicates that inefficiency outweighs the idiosyncratic disturbance term in accounting for total deviation from the frontier. Thus, technical inefficiency, and not stochastic error, is the main reason why vegetable farmers are operating below the production frontier.

3.3 Resource use efficiency of vegetable farmers

The technical efficiency levels were obtained using the estimator of Battese and Coelli (1988), that is, $TE = E\left[\exp(-\hat{u}_i) \mid \varepsilon\right]$. These scores are summarized in Table 2.

[Table 2 here]

The mean technical efficiency is 66.9 % indicating that about 33 percent of potential vegetable production is lost due to technical inefficiency. The range between the least efficient and the most efficient producer is quite wide. This shows that the technical efficiency of the average farmer can be increased substantially. Eighty percent of the farmers were more than 50% technically efficient. The efficiency levels of 25.4% of all the farmers sampled range between 71 and 80%, while 21.1% of them range between 81 and 90% technical efficiency.

3.4 Determinants of technical inefficiency of vegetable farmers

The estimated parameters of the inefficiency effects model used to identify the drivers of technical inefficiency are presented in Table 3. The results showed that the gender of the farmer, level of education and the net operated area could significantly influence farmers' technical efficiency.

4 Discussions

Female vegetable farmers are found to be more technically efficient than male farmers. This stems from the fact that women are more concerned about vegetable production which relates directly to household food security especially nutrient-rich traditional African vegetables. Hence, they have accumulated more experience in cultivating these crops compared to their male counterparts, who are generally more engaged in cash crop production such as cocoa and coffee. This result however needs to be cautiously interpreted given that the male-to-female ratio of the vegetable farmers that were interviewed during the field data collection shows an imbalance. As noted earlier, women comprised only 17% of the sampled respondents, while men constituted 83%. Nevertheless, our findings are in accordance with the results of Zavale *et al*. (2005) and Al-hassan (2008).

The level of education positively affects vegetable farm technical efficiency. Farmers who have at least attained secondary level of education are more technically efficient than those who have merely received primary education or no formal education at all. A high level of education subsequently increases the farmers' ability and propensity to adopt new ideas and techniques of production (Bidogeza *et al.* 2009).

[Table 3 here]

Farm size (area used for vegetable production) has a significant negative impact on technical efficiency. This confirms the famous assertion of an inverse relationship between farm size and productivity/efficiency, especially with respect to developing countries (Yotopoulos *et al.* 1970; Lau and Yotopoulos 1971; Larson *et al.* 2014**;** Henderson 2015; Ali and Deininger 2015). Most farmers in low-income countries are faced with limited resources such as insufficient capital and poor technical know-how. They therefore they tend to increase the size of their landholding in a bid to increase production. This is however not usually accompanied by higher input intensities (Dewbre and Borot *de* Battisti, 2008). So, our results corroborate the findings of Lau and Yotopoulos (1971) and Zavale *et al.* (2005). The former argue that small farms are easier to manage than large farms.

Farm ownership, location and access to credit were found to positively increase farmers' technical efficiency. The positive impact of farm ownership stems from the fact that those farmers who cultivate vegetables on farms which belong to them feel secure to undertake long-term investments on these farms than those who cultivate on rented or borrowed land. Also, our findings showed that vegetable farms located in Lower Pinyin, Menka, Buchi, Meforbe and Mbei were more efficient than those located in Santa, Baligham and Njong. This might be attributed to favorable soils and drainage conditions of the former. Other factors may have accounted for the efficiency differential. Farmers who had access to credit were relatively more efficient. Loans enabled them to acquire inputs such as farmyard manure, seeds and farm implements.

Technical efficiency tends to fall as the farmer gets older. However, age was not a statistically significant variable in our analysis. Khan and Saeed (2008) verified an inverse relationship between age and efficiency and found that older farmers are generally less informed and less receptive to new ideas and technologies. The results are however divergent with the findings of Mbanasor and Kalu (2008) and Mkhabela (2005) who contend that farmers become more experienced as they get older.

With respect to crop diversification, our results show that farmers who diversified vegetable species or who intercropped vegetables with tubers were less technically efficient than those who practiced vegetable monocropping. Although this result is not statistically significant, Rosenzweig and Binswanger (1993) point out that the quest for consumption smoothing and risk aversion sometimes leads farmers, especially the poorer ones, to choose asset portfolios which are less vulnerable to climatic variability, but that are less technically efficient. The negative impact of extension contact on technical efficiency also contradicts a priori expectation but this was statistically insignificant.

The results of this study lead to a certain number of relevant policy implications. Farmyard manure is very critical to vegetable production, especially where soils seem to be very poor. Thus, there is need for government and other stakeholders to improve farmers' access to manure. In addition, farmers need to be sensitized on the proper use of fertilizers, which initially should increase output, but whose misuse will end up reducing overall output while increase production cost. Extension agents need to be well trained in vegetable value chains to identify the specific problems faced by vegetable farmers in order to deliver quality extension services.

5 Conclusion

This study estimated the technical efficiency levels of vegetable farmers in Santa sub division, Northwest region of Cameroon and identified the prominent factors influencing technical efficiency. The Stochastic Frontier Analysis approach was adopted and the one-step procedure was used to estimate a truncated-normal Cobb-Douglas stochastic frontier production function and inefficiency model using cross-sectional data. The study is subjected to a couple of limitations arising mainly from the cross-sectional nature of the dataset, data collection and strong assumptions that have to be imposed for parametric modeling (distributional assumption and functional forms). The study's findings however provide insightful information on the nature and efficiency of smallholder vegetable farming in Cameroon.

The results have shown that manure, equipment, land ownership and labor could significantly increase the volume of vegetable production thereby increasing returns to scale. Our results indicated that significant possibilities exist to increase the efficiency of the average farmer. The findings also showed that younger and more educated farmers were significantly more efficient, meanwhile increasing the farm size could significantly reduce technical efficiency.

Significant collaboration to improve competitiveness and productivity in smallholder vegetable farming in Cameroon has been recorded over the years, notably between local research centers and universities on the one hand and international research centers on the other hand. However, getting the most out of such partnerships is contingent on properly functioning mechanisms that adequately disseminate and accelerate the uptake of research output.

Acknowledgements

The authors would like to thank Humidtropics (through The World Vegetable Center for leading this study) and all donors who supported this research through their contributions to the CGIAR Fund. For a list of Fund donors please see: http://www.cgiar.org/about-us/our-funders/. We sincerely thank all the participating small-scale farmers in Santa who freely provided the data for this study.

References

AGRA. 2015. *African Agriculture Status Report: Youth in Agriculture in sub-Saharan Africa.* Nairobi, Kenya. Issue No. 3.

Aigner D J, Lovell C K, Schmidt P. 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics,* **6**, 21–37.

Al-hassan S. 2008. Technical efficiency of rice farmers in Northern Ghana. *AERC Research Paper 178.* Nairobi: African Economic Research Consortium.

Ali D, Deininger K. 2015. Is there a farm size productivity relationship in African agriculture? Evidence from Rwanda. *Land Economics,* **91**, 317–343.

Bidogeza J C, Berentsen P B, De Graaff J, Lansink A M. 2009. Farm household typology for Umatara Province in Rwanda. *Journal of Food Security: The Science, Sociology, Economics of Food Production and Access to Food,* **1**, 321–335.

Binam J N, Gockowski J, Nkamleu G B. 2008. Technical efficiency and productivity potential of cocoa farmers in West African countries. *The Developing Economies,* **XLVI**, 242–263.

Bravo-Ureta B E, Pinheiro A E. 1997. Technical, economic and allocative efficiency in peasant farming. *The Developing Economies,* **34**, 48–67.

Caudill S B, Ford J M. 1993. Biases in frontier estimation due to heteroscedasticity. *Economics Letters,* **41**, 17–20.

Charnes A, Cooper W W, Rhodes E. 1978. Measuring the efficiency of decision making units. *European Journal of Operational Research,* **2**, 429–444.

Chavas J-P, Petrie R, Roth M. 2005. Farm household production efficiency: Evidence from the Gambia. *American Journal of Agricultural Economics,* **87**, 160–179.

Coelli T. 1995. Recent developments in frontier modelling and efficiency measurement. *Australian Journal of Agricultural Economics,* **39**, 219–245.

Coelli T,Battese G. 1996. Identification of factors which influence the technical inefficiency of Indian farmers. *Australian Journal of Agricultural Economics,* **40**, 103-128.

Dewbre J, Borot de Battisti A. 2008. *Agricultural Progress in Cameroon, Ghana and Mali: Why it Happened and How to Sustain it.* OECD Publishing.

Doffonsou R-A, Singh L S. 2014. *African Economic Outlook: Cameroon.* Tunis: African Development Bank.

Drechsel P, Keraita B. (Eds.). 2014. *Irrigated Urban Vegetable Production in Ghana: Characteristics, Benefits and Risk Mitigation* (2nd ed.). Sri Lanka: International Water Management Institute (IWMI).

FAO. 2013. *A Vegetable Garden for All* (5th ed.). Rome: Food and Agriculture Organization of the United Nations.

FAO. 2014. *Food and Nutrition in Numbers 2014.* Rome: Food and Agriculture Organization of the United Nations.

FAO. 2015. FAOSTAT. Online statistical database (Retrieved June 2, 2015) (available at http://faostat.fao.org).

Farell, M. J. 1957. The measurement of productive efficiency. *Journal of the Royal Statistical Society,* **120**, 253–290.

Haji J. 2006. Production efficiency of smallholders' vegetable-dominated mixed farming system in Eastern Ethiopia: A non-parametric approach. *Journal of African Economies*, **16**, 1–27

Henderson H. 2015. Considering technical and allocative efficiency in the inverse farm size-productivity relationship. *Journal of Agricultural Economics,* **66**, 442–469.

Jondrow J, Lovell C K, Materov I S, Schmidt P. 1982. On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics,* **19**, 233–238.

Kalirajan K P. 1981. An econometric analysis of yield variability in paddy production. *Canadian Journal of Agricultural Economics,* **29**, 283–294.

Khan H, Saeed I. 2011. Measurement of technical, allocative and economic efficiency of tomato farms in Northern Pakistan. *International Conference of Management, Economics and Social Sciences*, pp. 459-468. Bangkok.

Khor L Y, Zeller M. 2014. Inaccurate fertilizer content and its effect on the estimation of production functions. *China Economic Review,* **30**, 123–132.
Kodde D A, Palm F C. 1986. Wald criteria for jointly testing equality and inequality restrictions. *Econometrica,* **54**, 1243–1248.
Kopp R J, Smith V K. 1980. Frontier production function estimates for steam electric generation: A comparative analysis. *Southern Economic Journal,* **46**, 1049–1059.
Kumbhakar S C, Lovell C K. 2000. *Stochastic Frontier Analysis.* Cambridge: Cambridge University Press.
Kumbkakar S C, Wang H-J. 2010. Estimation of technical efficiency in production frontier models using cross sectional data. *Indian Economic Review,* **45**, 7–77.
Larson D, Otsuka K, Matsumoto T, Kilic T. 2014. Should African rural development strategies depend on smallholder farms? An exploration of the inverse-productivity relationship. *Agricultural Economics,* **45**, 355–367.
Lau L J, Yotopoulos P A. 1971. A test for relative efficiency and application to Indian agriculture. *American Economic Review,* **61**, 94–109.
Liverpool-Tasie S, Olaniyan B, Salau S, Sackey J. 2010. A review of fertilizer policy issues in Nigeria. *Working paper No. 0019 Nigeria Strategy Support Program.* International Food Policy Research Institute (IFPRI).
Lemba J, D'Haese M, D'Haese L, Frija A, Speelman S. 2012. Comparing the technical efficiency of farms benefiting from different agricultural interventions in Kenya's drylands. *Development Southern Africa*, **29**, 287–301
Mbanasor J A, Kalu K C. 2008. Economic efficiency of commercial vegetable production system in Akwa Ibom state, Nigeria: A translog stochastic cost function frontier approach. *Tropical and Subtropical Agroecosystems,* **8**, 313–318.
Meeusen, W., van den Broeck, J. 1977. Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review,* **18**(2), 435–444.
Mkhabela T. 2005. Vegetable efficiency in a vegetable based mixed-cropping sector in Tugela Ferry, Msinga District, Kwazulu-Natal. *Agrekon,* **44**, 187–204.
Murillo-Zamorano L R. 2004. Economic efficiency and frontier techniques. *Journal of Economic Surveys,* **18**, 33–77.
Nchare A. 2007. Analysis of factors affecting the technical efficiency of arabica coffee producers in Cameroon. *AERC Research Paper No.163.* Nairobi: African Economic Research Consortium.
Pitt M M, Lee L-F. 1981. Measurement and sources of technical inefficiency. *Journal of Development Economics,* **9**, 43–64.
Rejandran S, Afari-Sefa V, Karanga D K, Musebe R, Romney D, Makaranga M A. 2015. Technical efficiency of traditional African vegetable production: A case study of smallholders in Tanzania. *Journal of Development and Agricultural Economics,* **7**, 92–99.
Rosenzweig M R, Binswanger H P. 1993. Weather, weather risk and the composition and profitability of agricultural investments. *Economic Journal,* **103**, 56–78.
Shackleton C M, Pasquini M W, Drescher A W. (Eds.). 2009. *African Indigenous Vegetables in Urban Agriculture.* London, UK: Earthscan.
Thiam A, Bravo-Ureta B E, Rivas T E. 2001. Technical efficiency in developing country agriculture: A meta-analysis. *Agricultural Economics*, 235–243.
Unicef. 2013. Improving child nutrition. The achievable imperative for global progress. Nutritional report.
Uusiku N, Oelofse A, Duodu K, Bester M, Faber M. 2010. Nutritional value of leafy vegetables of sub-Saharan Africa and their potential contribution to human health: A review. *Journal of Food Composition and Analysis,* **23**, 499-509.
Yang R, Keding G. 2009. Nutritional contribution of important African vegetables. In C. Shackleton, M. Pasquini, A. Drescher, Eds. *African Indigenous Vegetables in Urban Agriculture*, pp. 105–135. London, UK: Earthscan.
Yotopoulos P A, Lau L J, Somel K. 1970. Labour intensity and relative efficiency in Indian agriculture. *Food Research Institute Studies in Agriculture, Trade, and Development,* **9**, 43–55.

Zavale H, Mabaya E, Christy R. 2005. Smallholders' cost efficiency in Mozambique: implications for improved maize seed adoption. *Staff paper 2005-04* , pp. 1−22. Ithaca, New York: Cornell University.

Table 1: Maximum Likelihood Estimates of the Stochastic Production Frontier Model for vegetable producers in Santa, Cameroon

Lnland	0.269**
	(0.132)
Lnlabour	0.262 *
	(0.153)
Lnmanure	0.463 ***
	(0.0995)
Lnfertiliser	-0.240 **
	(0.117)
Lnseed	0.154
	(0.0945)
Lnchemicals	-0.0520
	(0.0782)
Lnequipment	0.298 ***
	(0.0951)
Constant	8.003 ***
	(1.029)
Inefficiency variation (σ_u)	0.672
Noise variation (σ_v)	0.378
Signal-to-noise ratio (λ)	1.778
Observations	71
Log likelihood	-53.03

Note: Standard errors in parentheses; *** P<0.01, ** P<0.05, * P<0.1.

Table 2: Frequency distribution of technical efficiency levels of vegetable farmers

Intervals (%)	Frequency	Percentage
0-10	1	1.4
11-20	1	1.4
21-30	5	7
31-40	2	2.8
41-50	5	7
51-60	9	12.7
61-70	8	11.3
71-80	18	25.4
81-90	15	21.1
91-100	7	9.9
Sum	71	100
Mean		66.9
SD		21.4

Minimum	0
Maximum	94.7

Table 3: Maximum Likelihood Estimates of the Inefficiency Model
Dependent variable: Technical inefficiency variance

Age	0.00707
	(0.0243)
Sex dummy	1.875*
	(0.991)
Ownership dummy	-1.355
	(0.830)
Education dummy	-1.599**
	(0.711)
Area	0.000118**
	(5.16e-05)
Geographic location dummy	-0.641
	(0.657)
Credit dummy	-0.879
	(0.628)
Diversification dummy2	10.09
	(128.7)
Diversification dummy3	11.52
	(128.7)
Extension dummy	0.825
	(0.607)
Constant	-11.81
	(128.7)

Note: Standard errors in parentheses; ***, $P<0.01$, **, $P<0.05$, *, $P<0.1$.