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# Efficiency differentials in resource-use among smallholder cassava farmers in southwestern Cameroon

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**ABSTRACT**
Cassava has been identified as one of the staples that can reduce food security and help achieve the Sustainable Development Goal of "zero hunger". This article aims to estimate the efficiency levels of cassava producers in the Southwest region of Cameroon and to identify factors that account for efficiency differentials. The results show that, on average, cassava farmers are 64% technically efficient under the constant returns to scale and 96% under the variable returns to scale assumptions. The difference between the two models suggests the existence of scale inefficiency. Results also show that variables such as farm size, experience and land-use intensity are factors that significantly enhance the efficiency of cassava producers. A key recommendation is the need for policies that ensure increased access to agricultural land as well as secure tenure for cassava producers.

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## Introduction

Cameroon is predominantly agrarian and the exploitation of natural resources remains the driving force of the country's economic development (Tabe-Ojong and Molua 2017). Despite this reliance on agriculture, subsistence farming is predominant and unable to meet the increasing demand for food. The low production levels exacerbate hunger and the number of malnourished people. To this end, there has been renewed interest in understanding the causes of low production and yields in most agrarian economies; research and policy has sought to reverse this trend by identifying key efficiency and productivity drivers in a bid to attain the Sustainable Development Goal of "zero hunger". The key to increasing food production lies in raising agricultural productivity by improving the efficiency of resource use. Previous studies (Asefa 2011; Asante, Villano, and Batesse 2014) have identified technological improvements and technical efficiency as the main drivers of productivity increase. We therefore highlight the role of farmers' resource-use efficiency in improving farm productivity. In the face of novel technologies, the productivity of farmers can only improve if they are efficient in their current use of farm production inputs. Knowledge of optimal resource allocation and productivity of cassava farmers will benefit cassava producers in resource re-allocation for maximum yield, and will provide evidence-based policy development on resource use and equitable resource allocation in all sectors of the economy.

Cassava is a shrubby tropical crop known mainly for its starchy tuberous root that is a major source of carbohydrates. Other uses include the production of flour, *garri* (a variant of tapioca in fried granular form, common in West and Central Africa) and organic manure from the tuber peelings. Given its multipurpose use, cassava is usually cultivated, mostly by smallholders, for both food (sweet cassava) and as a cash crop (bitter cassava). In terms of consumption, cassava is one of the main sources of food carbohydrates, alongside rice and maize. It is also regarded

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as a principal cash crop with huge potential to boost economic growth given its contribution to the agricultural incomes of smallholder farmers (Girei and Dire 2013). Cassava serves as a staple either in its pure or processed form (IITA 2005) with more than 80% of rural and urban families consuming cassava and cassava-derived products daily (Essono et al. 2008). In addition to this, cassava leaves are an important source of proteins, vitamins and minerals. Today, cassava has become an important marketable produce because of increased industrial demand from abroad, as it can be processed into *garri*. Cassava products such as *bobolo*, flour, starch paste, *garri, fufu* and *chikwangue* are increasingly sold within Cameroon and other African countries (Njukwe et al. 2012).

In Cameroon, cassava is ranked first among root and tuber crops in terms of total production and consumption. Annual production is estimated at 2.3 metric tonnes, with the Centre, East and South regions dominating production (PNDRT 2005). Despite this positive production record, a significant yield gap exists between commercial cassava producers who produce as much as 90 tonnes/hectare and smallholder farmers who only produce about 10 tonnes/hectare. One of the reasons for this yield gap is that most smallholders (who cultivate mostly for consumption, with only marginal marketable surplus) use rudimentary farm tools and traditional production technologies which are low-yielding. This is compounded by the fact that smallholder farmers find it difficult to participate in output markets because of a range of constraints and barriers reducing their incentives to commercialise. These may be reflected in hidden costs that make access to markets difficult. Smallholder farmers also lack the necessary assets (inputs) and knowhow, have poor facilities and are usually faced with information asymmetry, especially unreliable market information. All these impinge on their use of inputs and their managerial abilities.

Efficiency is a relative concept measured by comparing the actual ratio of outputs to inputs with the optimal input-output ratio (Thi 2013). It can be defined as the relative performance of the processes used in transforming a given set of inputs into outputs. Three main dimensions of efficiency are identified in the literature: technical, economic, and allocative efficiency. Technical efficiency measures the ability of a farmer to obtain maximum output from a given set of inputs (output-oriented measure); or use the minimum feasible amount of inputs to produce a given level of output (input-oriented measure). Allocative efficiency measures the ability of a farm-firm to use inputs in optimal proportions given their respective prices and the production technology. Economic efficiency is the product of technical efficiency and allocative efficiency. A farmer who is both technically and allocative-efficient is said to be economically efficient. Economic efficiency is thus defined as the capacity of a farm-firm to produce a predetermined quantity of output at minimum cost for a given level of technology (Poudel et al. 2015).

Farm efficiency has been empirically investigated with the use of different techniques as well as for different crop types. There is considerable empirical literature on resource-use efficiency in sub-Saharan Africa, with most studies focusing on staple grains like maize, beans and rice (Binam, Tonye, and Wandji 2005; Asefa 2011; Ogada et al. 2014; Mango et al. 2015; Boubacar et al. 2016; N'cho et al. 2017; Ng'ombe 2017). Increasingly, attention has been given to vegetables (Akamin et al. 2017) and most recently to root and tuber crops like cassava and yams (Asante, Villano, and Batesse 2014; Okoye et al. 2016). In a bid to gauge the effect of the adoption of the improved yam minisett technology on the technical efficiency of yam farmers in Ghana, Asante, Villano, and Batesse (2014) employed the stochastic frontier approach and found farmers' mean technical efficiency scores to be 85% and 89% in the Ashanti and Brong Ahafo regions, respectively. The authors found technology adoption to positively drive technical efficiency in the Ashanti region, but negatively in the Brong Ahafo region.

Despite the importance of cassava for food security and income generation, very little is known on the efficiency and productivity level of cassava farmers in sub-Saharan Africa. Okoye et al. (2016) set out to understand efficiency differentials among cassava farmers in Madagascar. They estimated and found individual farm-level technical efficiency to be 79% and driven mainly by the educational level, gender and age of the farmer. However, technical efficiency may also be driven by the level of use of farm productive inputs, particularly land, labour and capital. In this light, we complement and provide new insights into the productivity and efficiency of cassava production. Cameroon is a relevant case study given the increasing number of youths involved in cassava production and the government's goal to scale up production and provide processing facilities. No study on the efficiency of cassava farmers from a rainforest tropical climate has been undertaken, to the best of our knowledge. So, while this study is relevant for a cassava-producing economy like Cameroon, it also provides insights to guide policymakers in other potential cassava-producing areas in sub-Saharan Africa.

Moreover, most of the aforementioned studies are based on the parametric approach to efficiency measurement. This approach allows for hypothesis testing through the specification of a functional form. Misspecification of this functional form could, however, lead to biased and inconsistent estimates for technical efficiency. The data envelopment analysis (DEA) technique is an alternative that does not require the specification of a functional form as it is a non -parametric method that relies on mathematical programming.

Based on the established empirical gaps, this analysis employed the DEA technique to investigate how farm-level characteristics like farm size and land-use intensity influence the technical efficiency of cassava producers. Specifically, we seek answers to the following questions: (1) What is the technical efficiency level of cassava farmers in Cameroon? (2) What is the nature of their returns to scale? (3) What are the production, socio-economic and institutional factors that influence the observed level of technical efficiency (or account for inefficiency) of cassava producers? We hypothesise that, "there is no significant difference in efficiency among cassava producers", and further that, "there exists no significant relationship between efficiency and farmer-related socio-economic, production and institutional factors". Given the importance of cassava as a staple in Cameroon, studying the efficiency and productivity of cassava farmers is vital in order to reverse the problem of low productivity which mainly arises from resource-use inefficiency.

## Materials and methods

### *Study area and data*

The study was conducted in the Southwest region of Cameroon, an area of 24,910 km$^2$ representing 5.2% of the surface area of Cameroon. It has a population of 1.2 million people, with 70% of households having farming as their primary occupation. The area has an equatorial and sub-equatorial climate characterised by heavy rainfall (average of more than 2000 mm/year), a long rainy season (at least three months), high relative humidity (generally about 85%), and high temperatures of above 22°C on average (MINADER 2010). The main export and food crops are rubber, tea, cocoa, coffee, plantains, cocoyams, yams, cassava, maize and palm oil. Its 250 km-long coastline and dense river network provide substantial fish and seafood potential. Forest resources are also important, with the Korup National Forest Reserve harbouring a large variety of animal and plant species. The total number of farm households is estimated at 141,000 (Boris, Bloom, and Lyne 2009). As in most parts of the country, small farms are dominant in the region. About 45% of farms are between 0.5 and 2 hectares in size, with only about 30% of farms between 2 and 5 hectares. The Southwest region has a surface area of 951,316 hectares under cultivation, representing 38.2% of its total area. The region is home to an active volcanic mountain, which gives rise to rich volcanic soils (Nkembi 2004). The vegetation is dominated by patches of montane and sub-montane forests and grassland (Fonge, Tchetcha, and Nkembi 2012). The capital of the region is Buea and it is divided into six administrative divisions: Fako, Meme Manyu, Kupe-Manengouba, Lebialem and Ndian.

The analysis uses primary data obtained through interviews with cassava farmers. The main survey instrument used was a structured questionnaire, divided into four sections to capture data pertaining to the demography of respondents, household characteristics, institutional factors and factors of production. Multipurpose sampling was employed, comprising stratified, purposeful, and then simple random sampling. From the six divisions in the region, three were purposely chosen based on their agricultural inclination – Fako, Meme and Lebialem. Next, 50 cassava farmers were then randomly selected from each division, giving a total sample of 150. The localities sampled in Fako were Mile 16, Mutengene, Tiko, Yoke and Owe; those sampled in Meme divisions were Barombi native, Kosala, Fiango, Kake and Mabanda; Essoh-Attah, Menji, Foreke Down, Nkah and Alou were the areas sampled in Lebialem.

## *Measurement of efficiency*

This study uses two-stage data envelopment analysis (DEA).[1] DEA measures the relative efficiency of a decision-making unit (DMU) for both single input/output and multiple inputs/output cases. Efficiency could also be defined as the ratio of the weighted sum of outputs over the weighted sum of inputs. The DEA technique constructs a non-parametric piece-wise frontier over the data by using linear programming. A DMU (producer or farmer) has an efficiency score of 1 when the production level is on the frontier. Efficiency can be calculated from an input-orientation or output-orientation perspective. For input orientation, technical efficiency addresses the question: “By how much can inputs be proportionally reduced without reducing the output quantities produced?” Likewise, an output-oriented technical efficiency approach focuses on maximising the output quantities and addressing the question: “By how much can output(s) be increased without increasing the input quantities used?” (Farrell 1957).

DEA concepts have developed into many models, depending on the type of questions that are asked. In the early literature, Charnes, Cooper, and Rhodes (1978) proposed a constant returns to scale (CRS) model, while Banker, Charnes, and Cooper (1984) introduced the variable returns to scale (VRS) model. In addition, the DEA linear programming programme could either take a primal or a dual formulation. We employed the two-stage approach where we first calculate the total technical efficiency and scale efficiency scores of our sampled cassava producers using linear programming. Technical efficiency scores are obtained by estimating both a constant returns to scale DEA model and a variable returns to scale DEA model. Technical efficiency scores obtained from the constant return to scale DEA model are referred to as total technical efficiency, while those from the variable returns to scale DEA model are called “pure” technical efficiency scores. Scale efficiency measures the optimality of the farm-firm’s size. It is obtained by dividing the total technical efficiency by pure technical efficiency (Coelli et al. 2005). In the second step, the VRS efficiency scores are regressed on a set of variables posited to be important efficiency determinants.

For cassava farmers in the Southwest region of Cameroon faced with limited resources such as farm chemicals, poor-quality cassava cuttings, capital, availability of (un)skilled farm labour, and land constraint, an output-oriented DEA approach is more appropriate to describe the production possibility situation. It enables us to determine the maximum amount of cassava that is producible using the set of inputs available. Moreover, due to the existence of imperfect competition, credit constraints and a host of other factors, most cassava farmers may not be operating at optimal scale. Hence, we adopted the VRS DEA model which is more appropriate for analysing technical efficiency under such circumstances despite its inability to account for shocks arising from the weather parameters such as heavy rainfall, high relative humidity and high temperatures.

Suppose there are $n$ homogenous DMUs, and each DMU$i$ ($i = 1, 2, 3, \ldots n$) uses $s$ number of inputs($s = 1, 2, 3, \ldots n$) in order to produce $r$ outputs ($r = 1, 2, 3, \ldots n$). The following linear equation developed by Banker, Charnes, and Cooper (1984) can then be estimated in order to maximise the level of weighted outputs subject to the weighted inputs:

$$\text{Max}_{uv}{:}\theta = \mu_1 y_{1i} + \mu_2 y_{2i} + \cdots + \mu_r \mu_{ri} \tag{1}$$

subject to:

$$v_1 x_{1i} + v_2 x_{2i} + \cdots + v_s x_{si} = 1 \tag{2}$$

$$\mu_1 y_{1j} + \mu_2 y_{2j} + \cdots + \mu_r y_{rj} \leq v_1 x_{1j} + v_2 x_{2j} + \cdots + v_s x_{sj} \tag{3}$$

$$\forall_i \ \mu_i, v_i \geq 0 \text{ and } i, j = 1, 2, 3, \ \ldots, k$$

where $\theta$, technical efficiency; $i$, DMU; $y_{ri}$, the amount of output $r$ produced by $i$th DMU; $x_{si}$, the amount of inputs used by $DMU_i$; $\mu_r$, weight given to output $r$; $v_s$, weight given to input $s$

DMUs often face financial constraints or imperfect markets. To account for these effects, the VRS DEA model of Banker, Charnes, and Cooper (1984) was used. The envelopment form of the output-oriented VRS DEA model is specified as:

$$\text{Max}_{Q\lambda} \emptyset$$

Subject to:

$$\begin{aligned} & x_i - X\lambda \geq 0 \\ & \quad -\emptyset y_i + X\lambda \geq 0 \\ & N1'\lambda = 1 \\ & \lambda \geq 0 \end{aligned} \tag{4}$$

Given the restriction $N1'\lambda = 1$

$N1'$= convexity constraint which is an $N \times 1$ vector of ones.

$\lambda = N \times 1$ vector of weights (constants) which define the linear combination of the peers of the $i$th DMU.

$\frac{1}{\emptyset}$ = technical efficiency score which ranges between zero and one.

If $\emptyset = 1$, then the DMU is on the frontier and is technically efficient whereas, if $\emptyset < 1$, then DMU lies below the frontier and is technically inefficient.

The variables used in the DEA are defined as follows: cassava production (in tonnes) denoted as $y$; $x_1$ is fertiliser (kg); $x_2$ denotes farm size (hectares); $x_3$ is cassava cuttings (in bundles); $x_4$ is labour (man-days); $x_5$ measures financial capital (FCFA); $x_6$ captures land-use intensity (total quantity of land available to the farmer divided by the amount of land used for annual cropping); $x_7$ is pesticides (litres); $x_8$ is the extent of land fragmentation (number of plots); $x_9$ is education (years of schooling).

Computed technical efficiency (TE) scores are decomposed into two components; "pure" technical efficiency and scale efficiency. This may be done by running both a CRS and a VRS DEA upon the same dataset. Scale efficiency (if it exists) can then be computed as follows:

$$SE_i = (TE_{i,\,CRS}/TE_{i,VRS}) \tag{5}$$

$SE = 1$ indicates scale efficiency or constant return to scale (CRS) and $SE < 1$ indicates scale inefficiency. Scale inefficiency arises due to the presence of either increasing returns to scale or decreasing return to scale.

### *Efficiency drivers in cassava production*

The next step of our analysis was to examine the influence of socio-economic, demographic and other farmer-related characteristics on the technical efficiency of cassava farmers. The bounded nature of the efficiency scores dictates the need for an appropriate estimation technique: in this case the (two-limit) Tobit model which is appropriate for models with truncated or censored regressands. In certain cases, ordinary least squares (OLS) is used as a workable substitute.

Thus, with efficiency thresholds at zero and one, our two-limit Tobit is given as:

$$Y_i^* = \beta_0 + \sum_{1}^{9} (\beta_j Z_j + u_{ij}) \tag{6}$$

$$Y_i = \begin{cases} 1, & \text{if } Y_i^* \geq 1 \\ Y^*, & \text{if } 0 < Y_i^* < 1 \\ 0, & \text{if } Y_i^* \leq 0 \end{cases} \tag{7}$$

where $i$ refers to the DMU; $y_i$ is efficiency score of the $i$th DMU; $Y_i^*$ is a latent variable; $B_j$ are parameters to be estimated; $u_{ij}$ is the error term; $z_1$, Experience of the respondent (number of years the farmer has cultivated cassava); $z_2$, Household labour size (number of household members supplying labour in cassava production); $z_3$, Farm size (hectares); $z_4$, Fragmentation (number of cassava plots); $z_5$, Crop diversification (number of crops cultivated alongside with cassava); $z_6$, Credit access (1 for those who had access to credit and 0 otherwise); $z_7$, Land use intensity (total quantity of land available to the farmer divided by the amount of land used for annual cropping); $z_8$, Age of farmers (years); $z_9$, Education (years of schooling)

## Results

### *Efficiency scores*

The farmers' technical efficiency (TE) scores under the assumptions of constant return to scale (CRS) and variable return to scale (VRS) were estimated using output-oriented DEA. The results show that the average farmer has a technical efficiency level of 64% with the CRS model and 96% under the variable returns to scale model. The difference between VRS and CRS TE indicates the existence of scale inefficiency among the sampled farmers. The technical efficiency levels under VRS ranged from 0.540 to 1 and from 0.081 to 1 under CRS.

The difference between the technical efficiency under VRS and CRS is indicative of the presence of scale inefficiency (sub-optimality in terms of size of production). The scale efficiency scores (obtained by dividing CRS technical efficiency by VRS technical efficiency) range from 0.098 to 1, with a mean of 0.67. The relative CRS and VRS efficiency graphs (Figure 1) show that technical efficiency level of all farms is higher under VRS than CRS and this difference is attributable to scale inefficiency. From Figure 2, we observe that 71% of the sample cassava producers experience increasing returns to scale, 23% decreasing returns to scale, and 6% constant returns to scale.

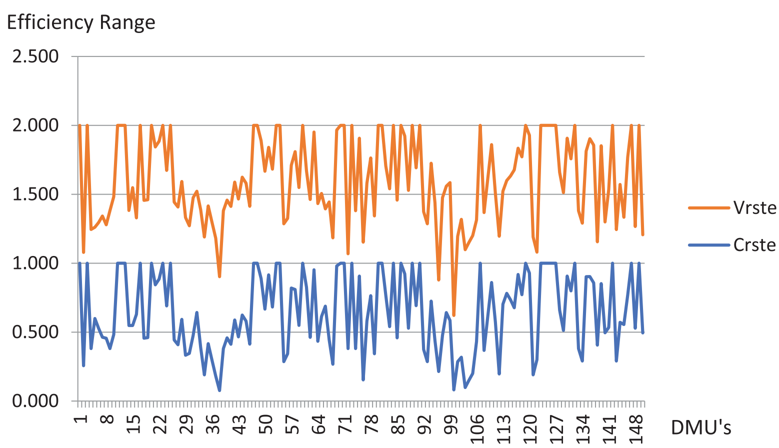


**Figure 1.** Relative CRS and VRS technical efficiency of the cassava farmers. Source: Authors' construction, 2018.

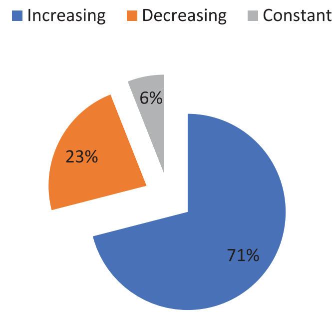


**Figure 2.** Returns to scale. Source: Authors' construction, 2018.

The average scale efficiency score of all farmers is 0.67 which implies that even when technically efficient, about 33% of farmers do not operate their farms at optimal sizes. The CRS and VRS technical efficiency scores show that of the three efficiency measures (CRS TE, VRS TE, and scale efficiency), technical efficiency scores under the CRS assumption show the least estimates (Table 1).

Frequency distributions for total technical efficiency (TE CRS), pure technical efficiency (TE VRS), and scale efficiency of the sample farms are presented in Table 2. The influence of scale (in)efficiency is evident, as revealed by the difference between the skewness of the technical efficiency scores of the CRS model and those from the VRS model. More than 96% of pure technical efficiency scores (from VRS model) lie above the 70th percentile, while only about 31% of the farmers are shown to be technically efficient based on the CRS assumption. It is also observed that while the CRS reports more than half of the sampled farmers as being less than 45% technically efficient, the VRS model shows that no cassava producer had a (pure) technical efficiency level as low as this. In terms of scale efficiency, about 33% of the farmers operated at (near) optimal farm size (that is, with a scale efficiency of more than 90%).

### *Determinants of technical efficiency of cassava producers*

Table 3 presents the results of the two-limit Tobit model for factors affecting the efficiency of cassava producers. The choice of Tobit over ordinary least squares stems from the distribution of the efficiency scores which lie between 0% and 100%. The econometric results reveal that farm size, experience in cassava production, and land-use intensity have a significant influence on the efficiency of cassava producers.

## Discussion

The results in Table 3 reveal a statistically significant positive relationship between farm size and technical efficiency. This finding aligns with those of recent studies (Gourlay, Kilic, and Lobell 2017) that rebut the oft-touted inverse farm size-productivity relationship that has pervaded the productivity literature. Despite this alignment, it is worth stating that we used the self-reported yields of farmers as well as the reported plot sizes, as opposed to the above studies. These studies made use of global positioning systems (GPS) for effective plot measurements as well as the novel crop

**Table 1.** Summary statistics of efficiency scores.

| Efficiency | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| CRS TE | 0.64 | 0.28 | 0.08 | 1 |
| VRS TE | 0.96 | 0.09 | 0.54 | 1 |
| Scale efficiency | 0.67 | 0.28 | 0.09 | 1 |

Source: Authors' computation based on field data (2018).

**Table 2.** Distribution of technical efficiency of sample.

| Range | Frequency | | | Percentages (%) | | |
|---|---|---|---|---|---|---|
| | TE CRS | TE VRS | Scale efficiency | TE CRS | TE VRS | Scale efficiency |
| 0.08–0.23 | 21 | 0 | 16 | 14 | 0 | 10.67 |
| 0.24–0.46 | 55 | 0 | 34 | 36.67 | 0 | 22.67 |
| 0.47–0.69 | 28 | 5 | 26 | 18.67 | 3.33 | 17.33 |
| 0.70–0.92 | 27 | 22 | 25 | 18 | 14.67 | 16.67 |
| 0.93–1.00 | 19 | 123 | 49 | 12.67 | 82 | 32.67 |

Source: Authors' computation (2018).

**Table 3.** Determinants of the technical efficiency of cassava producers.

| Variables | Coefficient | Standard error |
|---|---|---|
| Experience | −0.00769*** | 0.0024146 |
| Household labour size | 0.00935 | 0.0084392 |
| Farm size | 0.06843* | 0.0254139 |
| Land fragmentation | 0.00047 | 0.0221904 |
| Crop diversification | 0.00980 | 0.0145737 |
| Credit access dummy | 0.00832 | 0.0331975 |
| Land use intensity | −0.06149*** | 0.0198065 |
| Age | −2.56E-06 | 0.0008155 |
| Education | 0.02991 | 0.0204255 |
| Constant | 0.64471 | 0.0877596 |
| Log likelihood | 63156061 | |
| $R^2$ | 0.9657 | |
| LR Chi2(9) | 35.55 | |
| Prob > Chi2 | 0.000 | |

Notes: ***, ** and * denote significance at 1%, 5% and 10% level, respectively.

cut method of measuring farm yields. Crop cuts is a measurement technique which is motivated by the supposed over-reporting of high yields on small plots and the under-reporting of low yields on large plots. It has increasingly been recommended by FAO as the standard tool for yield measurement. Since yields are harvested by professional extension agents and on well measured plot sizes, systematic measurement errors are reduced, giving room for consistent and unbiased estimates. For our case, our measurements were carried out taking into account the necessary biases that wrong measurements may impose. Our results show that farmers who own large cassava farms are more efficient. Previous studies on productivity and efficiency analysis (Mango et al. 2015; Michler and Shively 2015; Latruffe et al. 2016; Akamin et al. 2017) have, however, found an inverse relationship, most probably because of measurement errors arising either from wrong plot size and yields reporting.

The coefficient of the land-use intensity is negative and statistically significant at 1%, indicating that the intensity of land use is likely to affect the level of technical efficiency of cassava farmers in the study area. This is probably because most cassava farmers are reliant on rented plots and thus focus on maximising the use of land in order to get the highest possible return from it. As such, yields begin to decline in subsequent years. In most cases, the plots and farms are small in size. Our finding of a negative influence of land-use intensity on farmer efficiency corroborates that of Thi (2013) who found a negative relationship between land-use intensity and the level of technical efficiency in the Northern region of Vietnam. When the intensity of land use is high, farmers tend to be actively engaged on that particular parcel of land with the heavy application of all required farm inputs. Farm management practices will also be optimal, leading to increased productivity and efficiency.

Surprisingly, and contrary to a priori expectations, experience depicts a negative impact on technical efficiency, implying that experience reduces technical efficiency. Experience is captured in efficiency studies using either the age of the household head or their active engagement in that particular farming system. We, however, considered both the age of the farmer and their years of experience in cassava cultivation. Both variables depict a negative relationship, but age is not significant. Experience should rather increase the technical efficiency of farmers as a result of the learning effect over time. Moreover, experienced farmers generally enjoy strong networks which they have developed over time with many key stakeholders involved in the product value chain. This gives them privileged access to improved technologies and improved farm inputs. In addition, experience should improve the resource allocative capacity of rural farmers. Our finding, however, fails to support this premise. About 59% of the farmers in our sample have cultivated cassava for more than 26 years, implying that most cassava farmers are relatively old. This is suggestive of the fact that, despite the farmers being very experienced, they lack the physical strength and energy for demanding and burdensome nature of cassava farming. Furthermore, most experienced farmers rely on their indigenous knowledge and experience built up over many years of producing cassava even with the advent of modern technologies and techniques in farm production. They prefer their local cassava breeds to the modern high-yielding cassava varieties, which are in most cases disease and pest resistant.

## Conclusion

This study set out to estimate the technical efficiency levels of cassava producers in the Southwest region of Cameroon and to identify factors that account for efficiency differentials. The data envelopment analysis technique was used to determine the level of technical efficiency of cassava producers, while the Tobit model was used to model the determinants of efficiency. The results showed a significant difference between the technical efficiency scores from the constant returns to scale model and those from the variable returns to scale model, indicating scale inefficiency in production. On average, the sampled cassava farmers are 64% technically efficient under the constant returns to scale assumption and 96% under variable returns to scale model. Furthermore, results from the Tobit regression showed that variables such as the experience of the respondent, farm size and land use intensity significantly influence the level of technical efficiency of cassava farmers in the study area.

Based on these findings, the following recommendations are made. Farmers experiencing increasing returns to scale should increase their use of inputs in production as this will more than double their output. In the same vein, farmers who experience decreasing returns to scale should reduce their variable input use in order to improve their efficiency levels. Smallholder cassava producers constitute an essential component of the agricultural sector which is vital for the country's development. From the analysis, it is evident that increasing the efficiency of smallholder farmers will go a long way to increase the production levels of the farmers, their productivity, farm income and thus contribute towards food self-sufficiency and rural welfare.

The following policy implications can be stated: first, since large farm sizes are more efficient than small farms, we propose that policy targets land access to households. Secured land tenure arrangements and tenure security should be provided to farmers. Furthermore, as households depict an increasing return to scale, which implies production can be increased by scaling up the use of various factor inputs like land and labour, the direction of the provision of land to farmers should be maintained. Moreover, production subsidies should be provided to farmers so that they can scale up production. Post-harvest storage and processing facilities should be included in the government's agenda to prevent post-harvest losses and enhance the sustainability of the value-addition process, which not only puts pressure on a more intensive production process but also provides an incentive for it.

To increase the productivity of the land, the use of sustainable agricultural intensification methods should be encouraged and taken up by farmers. Farmers should be provided with a complete packet of improved seeds and farming techniques to boost their production levels and increase productivity. Lastly, on the implications of the returns to scale, farmers should specialise more on cassava production and their managerial abilities. To aid specialisation, the government should provide ready-made markets for agricultural produce while providing advanced training to farmers.

## Note

1. The two-stage DEA in this context refers to the approach in the literature whereby a Tobit or ordinary least squares estimation is used to identify factors influencing efficiency. This is different from the connotation suggested by Coelli (1996) who uses it to define the manner in which slacks are dealt with (using a second LP problem, as opposed to the one-stage or multi-stage model).

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