AfJARE
African Journal of Agricultural and Resource Economics Volume 16 Number 1 pages 64-79

Stochastic meta-frontier function analysis of the regional efficiency and technology gap ratios (TGRs) of small-scale cassava producers in Liberia

Kollie B. Dogba*
Department of Agricultural and Applied Economics, College of Agricultural and Veterinary Sciences, University of Nairobi, Nairobi, Kenya. E-mail: kbdogba@yahoo.com

Willis Oluoch Kosura
Department of Agricultural and Applied Economics, College of Agricultural and Veterinary Sciences, University of Nairobi, Nairobi, Kenya. E-mail: kosura@uonbi.ac.ke

Chepchumba Chumo
Department of Agricultural Economics and Resource Management, School of Agricultural and Natural Resources, Moi University, Eldoret, Kenya. E-mail: chumbiin@gmail.com

* Corresponding author

Abstract

To enrich agriculture reform and reap its benefits, policy makers need to localise policy issues within and across their domestic zones. Using a stochastic meta-frontier function, this study analysed the production efficiency of the cassava subsector of cassava growers from Bomi and Nimba counties in Liberia. The paper contributes to the domestication of agriculture policy issues within a country. The study found different scales of production returns for cassava growers in Bomi and Nimba counties. Farmer age, gender, household size and access to credit were key determinants of the technical gap ratio of the cassava subsector. The study recommends that relevant stakeholders (in a multi-stakeholder partnership) design a holistic approach of innovative finance (including microfinance, agriculture insurance and a grouped loan scheme) and social enterprise development that will encourage more women and young people to grow cassava efficiently for the higher productivity of the cassava subsector.

Key words: cassava production; Liberia; small-scale farmers; stochastic meta-frontier function analysis; technology gap ratio

1. Introduction

Severe food insecurity still persists, and it poses challenges to the livelihoods of many people, especially the poor in Sub-Saharan Africa, Latin America and Southern Asia (Ville *et al*. 2019). Cassava has been a major intervening crop to food security during crises and force majeure situations because of its biological attributes, resistance to harsh environments, and prolonged storage of its roots (Nweke *et al*. 2002; Lebot 2009). More than 40 million Africans consume cassava daily in different forms. Across all tropical regions, cassava is cultivated either for staple food, animal feed or industrial purposes. With increasing demand in emerging Asian economies for cassava as an industrial input, there is an opportunity for African economies to optimise cassava for export gains, higher farm income and sustainable economic development (Nweke *et al*. 2002).

In Liberia, more than 90% of agricultural households cultivate cassava. The mean cassava output is estimated at between six and seven metric tonnes, lower than the regional mean of 10 to 18 metric tonnes (Coulibaly *et al*. 2014). To achieve food security, the Government of Liberia agricultural agenda seeks to stimulate domestic production and commercialise competitive agricultural commodities. The country has been structurally segmented into six agro-clusters and strategy has been developed for many crops and facets of the agriculture sector; yet, there is a scarcity of information on quantitatively measured efficiency levels of agricultural crops and their value chains (Ministry of Agriculture 2008; Zinnah 2016). This paper seeks to measure and assess the determinants of technical efficiency of cassava production in two of the six regions. The key objective of the study was to measure the mean regional technical efficiency (TE), technology gap ratios (TGRs) and meta-frontier technical efficiency (MTE) of small-scale cassava producers in Bomi and Nimba counties. The rest of the paper is organised as follows. Section 2 presents the methodology, analytical framework and the econometric approach. Section 3 gives the results. The policy implications and recommendations of the study are presented in Section 4, and Section 5 concludes the study.

2. Methodology

2.1 Conceptual framework

The conceptual framework of the study is presented in Figure 1 below. Intervening factors influenced the inputs into the production system to generate the cassava output, which is a pertinent variable used to determine the level of technical efficiency.

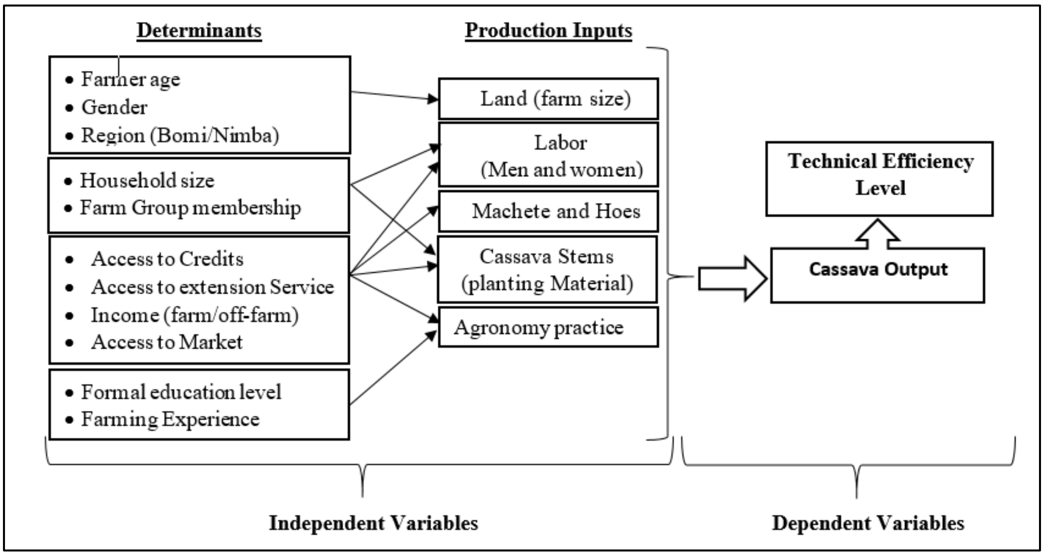

Figure 1: Conceptual framework of the study

Cassava production factors are land, labour and other inputs (stems, hoes, machetes and agronomy practices). The framework postulates that land is influenced by the farmer's age and gender and the region of the farm setting; labour is influenced primarily by the farmers' household size, and their involvement (or not) in farming groups. Other factors, such as access to finance, off-farm income, and access to extension services and markets also influenced the capability of farmers to hire labour. These factors, along with farmers' experience and formal education influenced the combination of inputs (cassava stems, machete, hoes and appropriate agronomy practices) for optimal cassava output and higher technical efficiency.

2.2 Study areas, data sources and data collection procedures

The study was conducted in two of the three profiled cassava sectors in Liberia. The Nimba cluster and western corridors account for intensive cassava production and local processing respectively. Nimba and Bomi counties were purposively selected from the Nimba cluster and the western corridors because the farmers here concentrate on cassava production. More than 250 kilometres apart, Nimba county lies northeast, bordering Cote D'Ivoire and Guinea, while Bomi sits northwest, near Monrovia, the capital city (shown in Figure 2). Eight districts (four from each of the counties) were purposively selected. Systematic random sampling from farmer listings was used to select 303 participants.

Primary data on farm inputs/output, socioeconomic and institutional variables was collected from farmers using the mobile Kobo® toolkits. With the involvement of the authors,[1] data was collected from May to June 2019. The collected data is associated with the 2018/2019 cassava farming year.

Figure 2: Political map of Liberia

Two teams, trained in the survey questionnaires and the data collection toolkits, set out concurrently to each of the regions of Bomi and Nimba. The teams were led by a survey assessor to interpret and localise the questionnaire during the training and data collection.

2.2 Measurement of variables

2.2.1 Dependent variables

The dependent variables are output, technical efficiency and technology gap ratios. Output measured in kilograms is the dependent variable, resulting from the use of inputs for all the production functions. Since cassava output aligns with the single-output production chain, it is a less cumbersome procedure to account for output (Coelli *et al*. 2005). The dependent variables for the inefficiency models of management and environmental factors are the technical efficiency scores and the technology gap ratios respectively. These variables fall within the interval of zero and one, and are invariant to units of measurement (Kumbhakar & Lovell 2000).

[1] Survey design, technical review and data collection were undertaken by WO Kosura and C Chumo. Data collection was supervised by KB Dogba. The data can be requested from the corresponding author.

2.2.2 Independent variables

The farm, stem cuttings, farm tools and labour are the inputs for cassava production functions. **Farm size** measures the hectare of area on which the cassava is produced. **Stem cuttings** measure the bundle of cassava cuttings/sticks used.[2] **Farm tools** represent the totals amount of machetes and digging hoes used during the production period; **labour** indicates the number of man-days (a minimum of five working hours) worked by labourers employed on the cassava farm.

Male labour and **female labour** were used to gauge the gender effect (male or female respectively) on labour used in cassava production. Other exogenous variables in the efficiency models are farmer's age (continuous), gender (female = 1, male = 0), formal education (in three categories), farming experience (continuous), group membership (No = 1, Yes = 0), household size (continuous), access to extension, access to credit (No = 1, Yes = 0) and distance to markets (continuous).

2.3 Analytical framework and estimation approach

2.3.1 Analytical framework

The meta-frontier analyses evolved from the concepts of Hayami and Ruttan (1971), namely that an agriculture meta-production function is an overlapping neoclassical production frontier enveloping other local production functions and environmental factors to suitably explain the dynamics of agriculture productivity between the local functions. This analytical framework was redefined by Battese and Rao (2002), Battese *et al*. (2004) and O'Donnell *et al*. (2008) in the adoption of a two-step procedure: first, by using a stochastic frontier analysis to determine each regional frontier, and next by using deterministic approaches (of either linear or quadratic programming techniques) to determine the meta-frontiers with simulated or bootstrapped standard errors. Criticising the redefined model of Battese and O'Donnell in the deterministic approach of the meta-frontier, Huang *et al*. (2014) showed that the simulated and bootstrapped standard errors were too large and unreliable for inferential statistics. Furthermore, Huang *et al*. (2014) proposed the adoption of a stochastic meta-frontier (SMF) because the parametric features in both the estimation of groups and the meta-frontier were realistic. The randomness of the SMF approach covers determinants of technical efficiency within groups and environmental factors of efficiency in relation to the meta-frontier. In the SMF model, the random shocks are core characteristics used to determine the estimates for the regional and the meta-production frontiers respectively.

As a requirement for using stochastic models, Huang *et al*. (2014) adapted the specification of functional forms for both the production functions of each region and the meta-production frontiers. Input and output data from cassava farmers in Bomi and Nimba counties were used to determine each of the regional technologies. The Battese and Coelli (1992) functional form was adapted to specify each group production frontier, using:

$$Y_{ji} = f^{j}(X_{ji})e^{v_{ji}-u_{ji}} = e^{X_{ji}\beta^{j}}e^{v_{ji}-u_{ji}}, \tag{1}$$

where j = 1 or 2; i = 1, 2, 3… I_j.

The input is X_{ji} and the output is Y_{ji} respectively for the ith farm within the *j* region (either in Bomi or Nimba county). $f^{j}(*)$ is the functional or transformation form of the production process for a specific group. β^{j} are the set parameters for each *j* region of cassava farmers.

[2] A cassava stem bundle contains 40 to 50 sticks, with a stick measuring 1 to 1.5 metres.

v_{ji} is the two-sided statistical noise, with $N(O, \sigma_v^{j2})$, while u_{ji} is the non-negative truncation error term of the inefficiency effect with $N^+\left(U^j(Z_{ji}), \sigma_u^{j2}(Z_{ji})\right)$.

$e^{(*)}$ accounts for the exponential growth of each *j* group's production frontier, and Z_{ji} indicates the determinants of the inefficiency of the production function for each *j* region of cassava farmers. This is done for each of the heterogeneous groups of Bomi and Nimba farmers.

Technical efficiency of each *j* group of cassava farmers was predicted using the maximum likelihood estimation (MLE) of the group production function (Jondrow *et al*. 1982). The specification is as follows:

$$TE_i^j = \frac{\mathrm{Y_{ji}}}{\mathrm{f^j(X_{ji})e^{v_{ji}}}} = \mathrm{e^{-u_{ji}}}, \tag{2}$$

with TE_i^j indicating the technical efficiency of the *i*th farm in the *j* group associated with exogenous group-specific determinants.

To determine the meta-frontier, estimates of the regional (or group) production functions were pooled. An ideal functional form was used to determine the meta-production frontier, on the assumption that the meta-frontier, at its lowest, is equal to or overlaps each of the regional production functions. This specification is expressly presented as:

$$\mathrm{f^j(X_{ji})e^{v_{ji}-u_{ji}}} = \mathrm{f^M(X_{ji})}\mathrm{e}^{\varepsilon_{ji}^M}, \tag{3}$$

where $\mathrm{f^M}(*)$ is the meta-production function such that $\mathrm{f^M}(*) \geq \mathrm{f^j}(*)$ for all *j* groups, and the *i*th farm. The ε_{ji}^M is the composite error of the meta-frontier, such that:$\varepsilon_{ji}^M = V_{ji}^M - U_{ji}^M$.

V_{ji}^M accounts for the statistical noise from the measurement and pooling of the estimates from the regional frontiers with similar properties as the v_{ji}, while the U_{ji}^M is the environmental inefficiency of the meta-frontier derived from the performance of regional frontiers. It is truncated normal with $U_{ji}^M \sim N^+\left(U^M(Z_{ji}), \sigma_U^{M2}(Z_{ji})\right)$; Z_{ji} indicates environmental determinants of the meta-frontier.

This environment gap (also called the technology gap ratio) is the ratio of the group frontier to the meta-frontier. The quasi-maximum likelihood (QML) procedure was used to estimates the technology gap ratio. The QML produces robust estimates of standard errors even for compiled data, joint and pooled estimates from estimation errors, and aggregation.[3] The technology gap ratio was estimated as follows:

$$\mathrm{TGR_i^j} = \frac{\mathrm{f^j(X_{ij})}}{\mathrm{f^M(X_{ij})}} = \mathrm{e^{-U_{ijt}^M}} \leq 1 \tag{4}$$

The meta-frontier technical efficiency score of farms indicates the variation om farm output to the meta-production frontier, which includes the gap and the farm efficiency, presented as follows:

$$\mathrm{MTE_{ij}} = \frac{\mathrm{Y_{ij}}}{\mathrm{f^M(X_{ji})}} = \mathrm{TGR_i^j} * \mathrm{TE_i^j} \tag{5}$$

[3] See Carroll *et al*. (1998) and White (1982) to further explore the properties and advantages of the QML to derive consistent estimates.

In summary, the variation in farm output to the regional frontier accounts for technical efficiency (TE); the technology gap ratio (TGR) is influenced by environmental factors (economic and non-economic) and is the gap between a group frontier and the overarching meta-frontier. TGR is group specific, although all the groups' TGRs are in relation to the meta-frontier. The meta-frontier technical efficiency (MTE) is the estimated gap between each "i" farm's output and the meta-frontier.

Figure 3 illustrates the relationship of farm output (A), regional frontier (B) and the meta-production frontier (C), and the relationship of the regional technical efficiency, technology gap ratio and the meta-frontier technical efficiency.

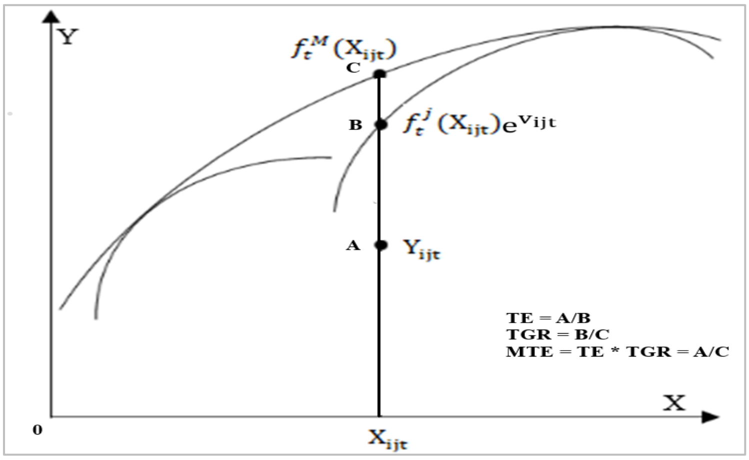

Figure 3: Stochastic meta-frontier production model

2.3.2 Estimation approach

To ascertain better functional forms and represent each group's and the meta-production frontiers, Cobb-Douglas and trans-log functional forms were subjected to verification. The linear association of variable test (t-test in Stata14), and the generalised likelihood tests, were performed on each regional dataset to ascertain the appropriate functional forms for estimation.

For the regional functions, the translog production function provided better fits. Technical efficiency scores were thus predicted from the joint MLE estimations of the stochastic production and inefficiency models. The translog production and technical efficiency models are presented as follows:

$$\ln Y_{est} = A + \sum_{i=1}^{5} \beta_i \ln(x_i) + 0.5 \sum_{i=1}^{5} \sum_{k=1}^{5} \beta_{ik} \ln(x_i) \ln(x_k) + (v_i) - u\left(\sum_{i=1}^{9} \delta_i Z_i\right), \quad (6)$$

where $\boldsymbol{Y_{est}}$ is the estimate of output; *i* is the farm input set (X_1 = farm size, X_2 = stems/cuttings, X_3 = farm tools, X_4 = male labour and X_5 = female labour), *k* is the interaction term and square terms (when I = k); and β_i and β_{ik} are the parameters of the single interactions and square terms. Z_i represents the set of inefficiency determinants, and δ_i is the parameter of the determinants (Z_1 = age, Z_2 = gender, Z_3 = formal education, Z_4 = household size, Z_5 = farming experience, Z_6 = main income source, Z_7 = access to market (km), Z_8 = access to extension, and Z_9 = group membership). This estimation was done separately for the Bomi and Nimba datasets.

Using similar testing techniques to select an adequate functional form, the Cobb-Douglas production function performed better than the translog functional forms, which did not converge and had insignificant interaction and square terms. From this Cobb-Douglas function, the technical gap ratio of the meta-production was predicted. The representation of the Cobb-Douglas meta-production is as follows:

$$\text{lnOutput}_{Est} = \text{A} + \sum_{i=1}^{5} \beta_i \ln(x_i) + (v_i) - u(\sum_{i=1}^{6} \delta_i Z_i), \text{ robust}, \quad (7)$$

where i is the farm input set (X_1 = farm estimates, X_2 = stem estimates, X_3 = farm tools estimates, X_4 = male labour estimates, and X_5 = female labour estimates), Z_i are the determinants of inefficiency, and δ_i is the parameter of the determinants (Z_1 = gender, Z_2 = farming experience, Z_3 = age of the farmer, Z_4 = access to extension, Z_5 = access to credits, and Z_6 = household size).

3. Results and discussion

3.1 Results: Technology gap ratio, technical and meta-technical efficiencies

The results of the study are presented in the tables (from Table 1 to Table 7). The results of the parameter stability test and the two-way statistical t-test for the variables are summarised in Tables 1 and 2 respectively. Tables 3 to 5 communicate the results of the estimation of the regions in the first-step stochastic frontier analyses (SFA) of technical efficiencies (TEs). Specifically, Table 3 presents estimates for the trans-log production frontier for the Bomi and Nimba regions. Table 4 summarises the statistics of the error term in the joint maximum likelihood estimations (MLE) of the production and inefficiency models, while Table 5 highlights the determinants of the regional technical inefficiencies. Tables 6 and 7 give the results of the meta-production frontier from the second-step SFA. In Table 6, the meta-frontier statistics of group technical efficiencies (TEs), technology gap ratios (TGRs) and the meta-frontier technical efficiencies (MTEs) are summarised. The estimates of the Cobb-Douglas meta-production function, and the determinants of the inefficiency model from the second-step MLE procedure, are listed and compared in Table 7.

Table 1: Test of parameter linearity (or stability) of the combined dataset

. test _b[reg_farm] = 0, notest
(1) reg_farm = 0
. test _b[region1] = 0, accum
(1) reg_farm = 0
(2) region1 = 0
F(2, 285) = 0.18
Prob > F = 0.8345

Note: reg_farm = interaction variable of region and farmland; region1 = the variable for the region (Bomi and Nimba)

3.2 Discussion

3.2.1 Descriptive statistics

From the results in Table 2 one can note statistical significance and equality of regional means for the following variables: cassava output, farm size, stem cuttings, farm tools, female labour, household size, and farming experience. The mean age of cassava farmers is 44 years, despite a significant difference between the regions. The mean household size of farmers' households located in Bomi and Nimba counties is six and nine persons respectively. The sample size is plausibly a reason why the study result is above the national household mean of 4.3 persons (LISGIS-RL 2017). The mean farm sizes are 1.58 and 1.36 hectares for cassava farmers in Bomi and Nimba respectively; this result indicates that the study participants were essentially small-scale cassava farmers (Rapsomanikis 2015).

Table 2: Comparison of descriptive statistics and regional means

Variable	Bomi [n = 87]	Nimba [n = 216]	Pool [n = 303]	t-value
	Mean	Mean	Mean	
Cassava output	1 188.51 (1 020.38)	1 506.02 (1 413.24)	1 414.85* (1 318.74)	-1.90
Farmland	1.58 (1.00)	1.36 (1.07)	1.42* (1.06)	1.67
Stem	28.86 (23.95)	43.63 (30.80)	39.39*** (29.73)	-4.01
Farm tools	6.40 (5.73)	7.84 (4.37)	7.43** (4.84)	-2.36
Male labour	21.53 (12.26)	22.66 (15.81)	22.33 (14.87)	-0.60
Female labour	8.34 (8.53)	20.78 (13.79)	17.21*** (13.70)	-7.83
Age	44.63 (14.14)	44.20 (13.41)	44.33 (13.60)	0.25
HH size	6.75 (2.78)	9.23 (3.98)	8.52*** (3.84)	-5.32
Experience	16.26 (11.29)	10.08 (8.31)	11.86*** (9.66)	5.26
Off-farm income	1,143.10 (3 902.19)	1,633.57 (5 876.88)	1,492.74 (5 382.73)	-0.72

*, ** and *** indicate level of significance at 10%, 5% and 1% respectively. Standard deviations are in parentheses

Farmers in Nimba plant more stems than their counterparts in Bomi. The mean number of cassava stems used by Bomi farmers is 15 bundles, which is less than the average number planted by Nimba farmers. The farming experience of farmers in Bomi is 16 years, and for farmers in Nimba it is 10 years. The mean cassava outputs of farmers in Bomi and Nimba are 1 188.51 kg and 1 506.02 kg respectively. The sum of the production input coefficient shows that the returns to scale (RTS) for farmers in Bomi and Nimba are 1.09 and -0.2 respectively. This indicates that farmers in Bomi are enjoying increasing return to scale (IRS) on their production technology, while farmers in Nimba are experiencing diminishing returns to scale (DRS) on their production function. According to this result, by increasing all factors of cassava production by 10, cassava farmers in Bomi can increase their cassava output by 10.9%, whereas farmers in Nimba are experiencing diseconomies of scale, which means that a 10% increase in all inputs together will decrease output by 2% (Debertin 2012).

3.2.2 Regional technical efficiency and determinants

Because the parameters for each of the regions were estimated separately based on the results from Table 1, the discussions of the efficiency of each group (regions) of cassava farmers in the following sections are considered mutually exclusive. Each of the regional production functions is distinct, with different production estimates for each input (Table 3) and different model statistics (Table 4). The mean technical efficiency of farmers in Bomi and Nimba counties was 0.5663 and 0.3603 respectively (Table 6). Because the parameters for each of the regions were estimated separately (Table 1), the discussion of the efficiency of each group (region) of cassava farmers in the following section are considered mutually exclusive.

3.2.2.1 Bomi Region

The mean technical efficiency of 56.63% for cassava farmers in Bomi county indicates that there was an average potential of 43.37% for farmers to increase output using the available inputs. Nearly 70% of the cassava farmers in Bomi have technical efficiency within four of the seven categories: 40% to 49%, 60% to 69%, 70% to 79% and 80% to 89%. Most cassava farmers had technical efficiency within the interval of 70% to 79% (Figure 4).

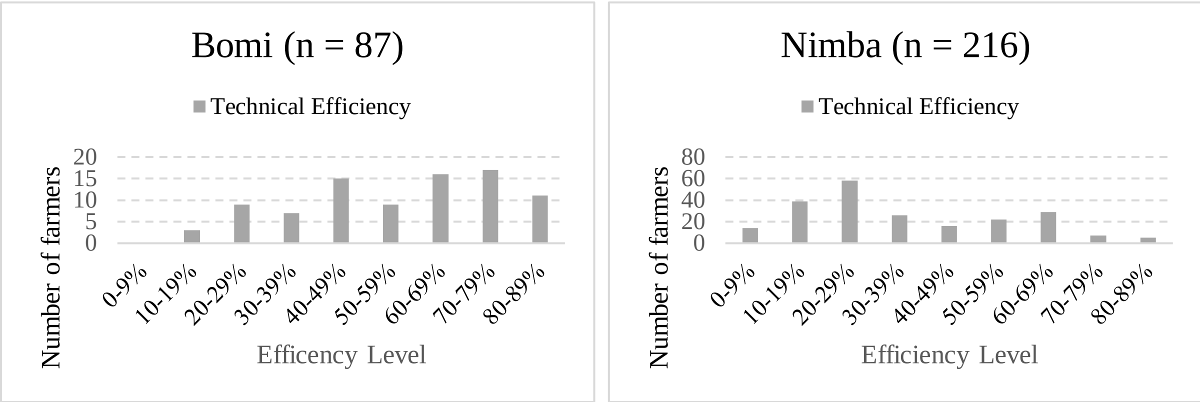

Figure 4: Distribution of cassava producers' technical efficiency by region

From Table 5, it is clear that significant determinants of the technical efficiency of farmers in Bomi are the age of the farmer, the gender of the farmer (dummy: Female = 1) and group membership (dummy: No = 1).

At the 0.05 level of significance, the age of a farmer is negatively significant in relation to technical efficiency, implying that the older a farmer becomes, the less dexterity he or she applies to labour-intensive cassava production. Technical efficiency of cassava production in Bomi is projected to decrease by 3% if farmers continue along the current line of input use for another farming year. Similar to this negative result, Khan and Saeed (2011) and Maina (2018) found that older farmers were economically inefficient, while younger farmers increased their technical efficiency. However, Handwerker (1981) and Nginyangi (2011) found that older farmers, who have more experience in farming activities, increased both productivity and economic efficiency. This unsettling trend in the results in terms of age is due to the levels of age productivity (Tauer 1995). Although there is a gap in research on age productivity in Liberia, this result shows that mean farmer age for cassava farmers in Bomi seems to be beyond the optimum age productivity of cassava farmers. Cassava farms owned by women signal a reduction in technical efficiency. At the 0.05 level of significance, technical efficiency will be reduced by 51% for every additional female farmer of a cassava farm. The dominant patriarchal customs and religious beliefs in the northwest region are plausible reasons impeding access to production resources by women. This aligns with the findings of the negative effect found by Udry *et al*. (1995) and Kinkingninhoun-Mêgagbé *et al*. (2010), in which female farmers experienced lower productivity – chiefly due to discrimination against women in relation to membership of schemes, land access and acquisition of resources.

Non-membership of farm groups has a positive effect on technical efficiency. At the 0.1 level of significance, an expected 48% increase in technical efficiency is realised if the farmer abandons group membership. This result implies that obtaining membership of a farm group reduces a farmer's time and efforts spent on his or her own cassava farm. Also, the challenges of free rides and opportunism posed by some group members during group labour frustrate many new members who intend to commit and old members who fully commit. This finding is in contrast to the expectation of the study, namely that group membership increases productivity, access to credit and support services (Maina 2018). However, it is in line with the findings of Gbigbi (2011) that cooperative membership has negative effects on economic efficiency.

Table 3: Estimates of the translog production frontier for cassava producers

	Bomi (n = 87)		Nimba (n = 216)		Pooled (n = 303)	
Variable	**Coefficient**	**Standard error**	**Coefficient**	**Standard error**	**Coefficient**	**Standard error**
Constant	5.10***	1.71	4.56**	2.08	4.91***	1.05
LnFARM	1.30	0.88	-2.12**	0.83	-0.50	0.46
LnSTEM	0.03	0.68	0.75	0.71	-0.46	0.36
LnFARMTOOLS	-0.34	0.74	-0.56	0.77	0.20	0.49
LnMALELAB	0.80	0.92	0.53	0.52	0.73*	0.40
LnFEMLAB	-0.40	0.59	0.72	0.59	0.61**	0.30
$LnFARM^2$	-0.06	0.17	-0.09	0.13	-0.07	0.09
$LnSTEM^2$	0.29	0.21	-0.12	0.19	0.21*	0.12
$LnFARMTOOLS^2$	0.04	0.29	0.49*	0.29	0.21	0.18
$LnMALELAB^2$	-0.13	0.33	-0.08	0.13	-0.15	0.12
$LnFEMLAB^2$	0.08	0.14	-0.03	0.14	0.02	0.07
LnFARMSTEM	-0.30	0.22	0.49**	0.19	0.21*	0.12
LnFARMTOOLS	-0.31	0.30	-0.22	0.16	-0.05	0.12
LnFARMLABM	0.17	0.29	0.18	0.14	0.05	0.12
LnFARMLABF	-0.20	0.13	0.06	0.15	-0.09	0.09
LnSTEMTOOLS	0.04	0.24	-0.13	0.18	-0.14	0.13
LnSTEMLABM	-0.10	0.25	0.17	0.12	0.15	0.10
LnSTEMLABF	0.05	0.11	-0.09	0.13	-0.02	0.06
LnTOOLSLABM	0.04	0.27	-0.16	0.15	-0.06	0.12
LnTOOLSLABF	0.08	0.15	0.15	0.18	0.03	0.08
LnLABMLABF	0.03	0.17	-0.15*	0.10	-0.18**	0.07
Return to scale	**1.09**		**-0.20**		**0.71**	

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

Table 4: Statistics of the error term from the frontier and efficiency estimations

	Bomi (n = 87)		Nimba (n = 216)		Pooled (n = 303)	
Variable	**Coefficient**	**Standard error**	**Coefficient**	**Standard error**	**Coefficient**	**Standard error**
Usigma Constant	-1.50*	0.81	-0.65**	0.30	-0.45	0.65
Vsigma Constant	-2.05***	0.69	-1.88***	0.52	-1.17***	0.26
Sigma_U (σu)	0.47**	0.19	0.72***	0.11	0.80***	0.26
Sigma_V (σv)	0.36***	0.12	0.39***	0.10	0.56***	0.07
Lambda (λ)	1.32***	0.30	1.85***	0.19	1.44***	0.27
$\gamma = \sigma u^2/(\sigma u^2 + \sigma v^2)$	0.6338		0.7746		0.6741	

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

Table 5: Determinants of technical efficiency

	Bomi (n = 87)		Nimba (n = 216)		Pooled (n = 303)	
Variable	**Coef.**	**Std. err.**	**Coef.**	**Std. err.**	**Coef.**	**Std. err.**
Constant	-0.48	0.99	0.61	0.74	-2.09	4.16
Age of the farmer	0.03**	0.01	0.01*	0.01	0.02*	0.01
Gender (1 = Female)	0.51**	0.26	-0.11	0.17	-0.29	0.57
Formal Education (y)	-0.01	0.03	-0.04**	0.02	-0.06	0.04
Household size	-0.04	0.05	0.00	0.02	0.00	0.03
Farming experience	-0.02	0.01	-0.05***	0.01	-0.06	0.04
Main income source (1 = From farm)	0.28	0.31	0.85**	0.42	2.44	3.53
Access to market (km)	0.02	0.01	-0.01	0.01	-0.01	0.02
Access to extension (1 = No)	0.11	0.22	0.59*	0.33	0.78	0.68
Group membership (1 = No)	-0.48*	0.27	-0.53**	0.20	-0.89	0.55

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

3.2.2.2 Nimba Region

In Nimba, there is an opportunity to increase the mean technical efficiency of production by 63.97%. As illustrated in Figure 4, farmers with the highest technical efficiency scores are within the category of 20% to 29%. Eighty percent of cassava farmers in Nimba have technical efficiency within the following five categories: 10% to 19%, 20% to 29%, 30% to 39%, 50% to 59% and 60% to 69%. Table 5 presents the significant determinants of technical efficiency among Nimba cassava farmers as follows: the age of the farmer, the years spent in a formal educational system, farming experience, main income source (dummy: 1 = Farm income), access to extension (dummy: 1 = No) and group membership (dummy: 1 = No).

At a level of significance of 0.1, the age of the farmer and non-access to extension services were statistically significant. Age had a negative effect on technical efficiency, with a magnitude of 1% for an additional year added to a farmer's age. This result validates the statistical indifference of the mean variable for "age of the farmer" in the regional and aggregated datasets. Non-access to extension services had a negative effect on technical efficiency. Lah *et al*. (2018) found that the adoption of, and not access to, extension services is the main challenge impeding cassava farmers in Nimba from acquiring extension services. Nevertheless, this result highlights the need for extension services for cassava farmers. The findings confirm those of Khan and Saeed (2011) and Coulibaly *et al*. (2014) that non-access to extension services reduces technical efficiency and productivity. At the 0.05 level of significance, the variables formal education, main income source and non-group membership significantly affect the technical efficiency of farmers in Nimba County. Formal education has an increasing technical efficiency effect of 11% for an additional year a farmer spends in a formal educational system. This indicates that, for an additional year of formal education, access to information is increased, more opportunities to take on non-farm jobs are available, and access to inputs and extension services is increased.

Depending on farm activity alone as a main source of income decreases technical efficiency by 85%. There is a negative effect of on-farm activity as the only source of major income. This gives rise to two reconsiderations: i) that farmers adopt and apply robust "agribusiness mentality" to the production of cassava, instead of keeping to the region's popular motive of producing cassava for sustenance purposes, and ii) that farmers seek out other non-farm jobs and businesses outside of the cassava production chains. This will smooth consumption and agricultural spending. Non-group membership has a positive effect on technical efficiency, with an increasing effect of 53% if a farmer drops another member from a farm group. Farming experience is significant at the 0.01 level of significance. With a magnitude of 5%, technical efficiency will increase for every further year of experience attained. This implies that, over time, farmers experiment and innovate as they constantly engage in cassava production. Over the years, these experiences have helped farmers to spare unnecessary resources. This result is in agreement with Adeyemo *et al*. (2010), Ogunleye *et al*. (2014) and Abdul-kareem and Sahinli (2018), namely that farming experiences support the technical, allocative and economic efficiency of cassava production.

Table 6: Analysis of regional efficiency scores and meta-frontier statistics

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
Bomi					
TE	87	0.5663	0.2050	0.1332	0.8740
TGR	87	0.9331	0.0809	0.7446	0.9995
MTE	87	0.5238	0.1863	0.1330	0.8491
Nimba					
TE	216	0.3603	0.2058	0.0437	0.8424
TGR	216	0.9329	0.0810	0.7035	0.9995
MTE	216	0.3390	0.1980	0.0336	0.8282
Pooled					
TE	303	0.5964	0.1994	0.0759	0.9002
TGR	303	0.9330	0.0808	0.7035	0.9995
MTE	303	0.3920	0.2117	0.0336	0.8491

3.2.3 Technology gap ratios, meta-technical efficiency and determinants

According to the results in Table 6, the TGRs fall within the range of 70.35% to 99.95%. This result identifies the range within which cassava inputs and resources can be optimised. The mean TGRs for farmers in Bomi and Nimba are 0.9331 and 0.9329 respectively (Table 6). The meta-frontier technical efficiency (MTE) of farmers in the regions vary from 3.37% to 84.9%, indicating a collapse from higher to lower efficiency levels (Figure 5). The result from Table 6 also show that the average MTE for the cassava subsector is 0.392, with regional MTEs for farmers in Bomi and Nimba at 0.5238 and 0.339 respectively. Farmers in Nimba have a higher opportunity to increase technical efficiency and optimise production using the existing cassava inputs within the cassava subsector. A comparison of regional, pooled and meta-frontier efficiency estimations showed differences. The estimations of the technical efficiency scores from the pooled dataset underestimated the technical efficiency scores derived from the regional datasets. This demonstrates the importance and ideal preference of the meta-frontier analysis to measure efficiency for datasets that signal heterogeneity (Alem *et al*. 2017).

From the results in Table 7, the significant environmental determinants of the meta-frontier are the age of the farmer, farming experience, gender of the farmer (1 = female), household size and access to credits (1 = no). At the 0.05 level of significance, the age of the farmer, household size and access to credits are significant. Although significant, age has a neutral effect on the technical efficiency of production in the cassava subsector. Household size has an increasing effect on technical efficiency, with a magnitude of 1%. This indicates that household size is a major labour source for cassava production, and larger households contribute a higher technical efficiency effect to the subsector's technical efficiency. This also amplifies the motive that cassava farming is mainly for sustenance and domestic animal feed. Hence, a big family, which has more labour, can contribute more labourers for the correct use of inputs.

Table 7: Estimates of the Cobb-Douglas meta-production frontier (N = 303)

Variables	Coefficient	Robust standard error	Z
Meta-production frontier			
Constant	1.52***	0.16	9.78
lnFARMest	0.05**	0.02	2.63
lnSTEMest	0.46***	0.04	10.57
lnFARMTOOLSest	-0.12	0.11	-1.09
lnMALELABest	0.34***	0.06	5.99
lnFEMLABest	0.09**	0.04	2.37
Environmental factors			
Constant	0.12	0.11	1.01
Gender (1 = Female)	-0.49***	0.15	-3.20
Farming experience	-0.01***	0.00	-3.93
Age of the farmer	0.00**	0.00	2.39
Access to extension (1= No)	-0.06	0.05	-1.05
Access to credit (1 = No)	0.09**	0.04	2.02
Household size	-0.01**	0.01	-1.95
Stochastic statistics			
Usigma_cons	-8.07***	0.71	-11.39
Vsigma_cons	-2.12***	0.15	-14.19
Sigma_u	0.02**	0.01	2.82
Sigma_v	0.35***	0.03	13.39
Lambda	0.05**	0.02	2.09

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

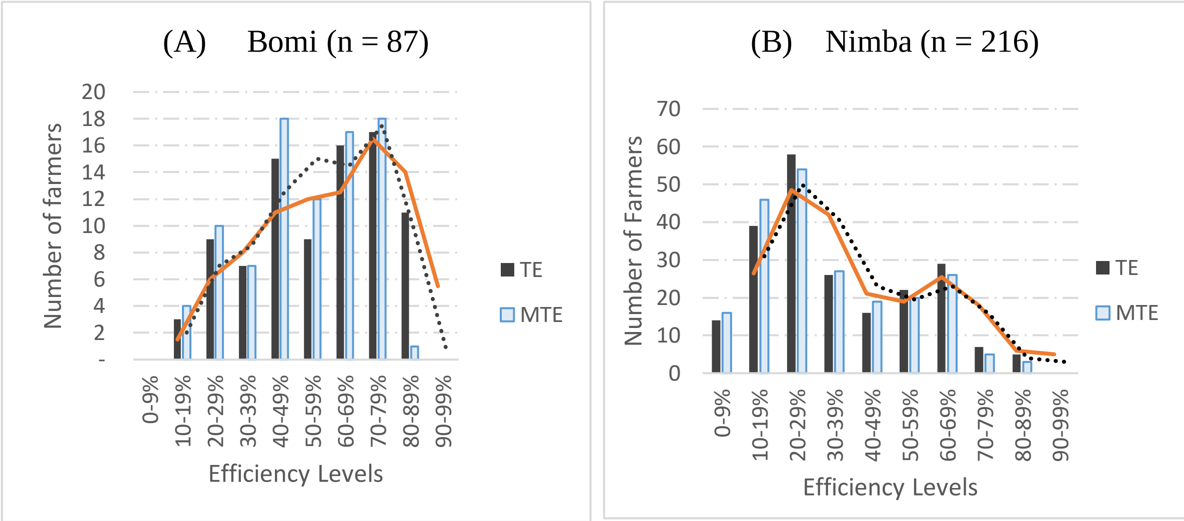

Figure 5: Meta-frontier analysis of regional (TE) and meta-technical efficiencies (MTE)

Non-access to credit, on the other hand, has a decreasing technical efficiency effect on the production of cassava within the expanded environment of the subsector. An additional cassava farmer experiencing financial exclusion and uneasy access to financial credits to capitalise on inputs and labour could cause the cassava subsector to experience a 9% drop in meta-frontier technical efficiency. Financial inclusion and low-interest credit empower farmers to acquire inputs faster and to pay for resources (of labour, equipment and extension services) for timely and prompt engagement in the production stages. Lacking access to credit deprives farmers of these opportunities, with an economic cost of low yields, lower income and a difficult livelihood.

At the 0.01 level of significance, the variables farming experience and gender (for female farmers) have positive effects on the technical efficiency of the cassava subsector. Farming experience has a magnitude of 1%. This result emphasises that, within the cassava subsector, cassava producers generally innovate and experiment as they farm from year to year, seeking to optimise planting material, farm tools and labour that are used to produce cassava.

The cassava subsector is expectant of an increasing effect of up to 49% if an additional female farmer is encouraged to enter into cassava cultivation. The result emphasises that female farmers commit more time and effort to their cassava farms than their male counterparts, despite the challenges women encounter with access to resources. This finding agrees with Alidou and Niehof (2013) and Twyman *et al*. (2015), who found that female farmers are more efficient and more productive than their male counterparts, even when their efforts and roles are not publicised.

4. Recommendations and policy implications

There is considerable advocacy for agriculture reforms to spur opportunities for, create economic jobs and support the sustainable economic development of African countries. However it may be, many policy makers rely on the generalisation of policy issues to all regions within their countries. From the analysis of the meta-frontier of Liberia's cassava subsector of growers in Bomi and Nimba counties, this is not the case; hence, the discussion below deals with worthy policy considerations to improve the technical efficiency of cassava production in Liberia.

- The result of female participation in the sector, which is strongly significant at 1%, has an increasing efficiency effect of 49%. This result stresses the need for more participation by women in cassava cultivation. Hence, with a national call for inclusive resource allocation and gender involvement in communal land governance, a policy is needed to apportion specific hectares to the production of rice and cassava. In rich cassava-producing regions (like Bomi and Nimba), female farmers should be given the land principally to produce cassava as a business for higher efficiency and productivity.

- At the 5% level of statistical significance, access to credit has a negative effect of 9% on the efficiency of the cassava subsector. From this result, innovative financing packages, including agriculture insurance schemes, local credit, social enterprise development and group loan schemes, are needed. Investment in irrigation and the modernisation of agriculture will assist cassava farmers to reduce farm drudgery, increase productivity and encourage young people to join the cassava subsectors as either farmers or as agri-entrepreneurs along the value chains.

- At the 1% level of statistical significance, farming experience has a positive influence on the cassava sector's efficiency. This result signals an opportunity to scale experience across the cassava subsector. Designing a project for experience-sharing among farmers who plant the same crops will improve overall efficiency. Efficient cassava farmers in Bomi county should be supported through a workshop to share their experiences with cassava farmers in Nimba and with extension officers. Such sharing of local knowledge about successful agronomy practices and experiences relating to cassava and other competitive crops, like rice, cocoa, chilli pepper, plantain and other vegetables, will improve the efficiency of the cassava sector in particular, and the agriculture sector in general.

- Finally, the study recommends the concerted and holistic partnership of all relevant agriculture stakeholders (in private, civil society and government institutions) to design innovative financial packages (including microfinance, agriculture insurance, collateral subsidy and loan schemes for women's groups) and social enterprise development initiatives (including capacity building, business skills and agribusiness) to modernise cassava production, and to attract more women and young people to cassava production to improve the efficiency of the subsector and the agriculture sector.

5. Conclusion

The stochastic meta-frontier production framework determines inferential estimates for both the regional and meta-production frontiers. From the different significant translog production function forms, technical efficiency levels for each of the regions were determined for cassava producers in Bomi and Nimba counties, although with no basis to compare these efficiency levels because of different locations and their levels of technology use.

The stochastic Cobb-Douglas meta-production function, which is ideal for the comparison of efficiency within regions, corrects for erroneous efficiency differences in the cassava subsector at 0.2044 (0.5964 to 0.3920). Significant meta-frontier determinants of cassava production within the cassava subsector are the farmer's age, farming experience, gender (1 = female), household size, and access to credit (1 = no). There is a need for a further research using a larger sample size study to assess the gender dynamics of cassava efficiency in the study areas.

Acknowledgements

The authors acknowledge the efforts of the survey assessors and enumerators, and the African Economic Research Consortium (AERC), for the research funding that supported the study. The authors also acknowledge the insights and rigor of the anonymous reviewer.

References

Abdul-kareem MM & Sahinli M, 2018. Demographic and socio-economic characteristics of cassava farmers influencing output levels in the Savannah Zone of Northern Ghana. African Journal of Agricultural Research 13(4): 189–95. https://doi.org/10.5897/AJAR2017.12268

Adeyemo R, Oke JTO & Akinola AA, 2010. Economic efficiency of small scale farmers in Ogun State, Nigeria. Tropicultura 28(2): 84–8.

Alem H, Lien G, Hardaker JB & Guttormsen A, 2017. Regional differences in technical efficiency and technological gap of Norwegian dairy farms: A stochastic meta-frontier model. Applied Economics 51(4), 409–21. https://doi.org/10.1080/00036846.2018.1502867

Alidou GM & Niehof A, 2013. Gender roles in cotton production and management of related organizations in Benin. Gender, Technology and Development 17(3): 313–35. https://doi.org/10.1177/0971852413498739

Battese GE & Coelli TJ, 1992. Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India. Journal of Productivity Analysis 3: 153–69. https://doi.org/10.1007/BF00158774

Battese GE & Rao DSP, 2002. Technology gap, efficiency, and a stochastic metafrontier function. International Journal of Business and Economics 1(2): 87–93.

Battese GE, Rao DSP & O'Donnell CJ, 2004. A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. Journal of Productivity Analysis 21: 91–103.

Carroll RJ, Ruppert D & Welsh AH, 1998. Local estimating equations. Journal of the American Statistician Association 93(441): 214–27.

Coelli TJ, Rao DSP, O'Donnell CJ & Battese GE, 2005. An introduction to efficiency and productivity analysis. Second edition. New York: Springer Science + Business Media.

Coulibaly ON, Arinloye D-DAA, Faye M, Abdoulaye T, Vodouhe F, Adjovi GM, Kakpo A & Bankole VNFH, 2014. Regional cassava value chains analysis in West Africa: Regional summary. Technical Report. https://doi.org/10.13140/2.1.2510.2403

Debertin DL, 2012. Agricultural production economics. Second edition. Lexington KY: Author.

Gbigbi MT, 2011. Economic efficiency of smallholder sweet potato producers in Delta State, Nigeria: A case study of Ughelli South Local Government Area. Research Journal of Agriculture and Biological Sciences 7(2): 163–8.

Handwerker WP, 1981. Productivity, marketing efficiency, and price-support programs: Alternative paths to rural development in Liberia. Human Organization 40(1): 27–39.

Hayami Y & Ruttan VW, 1971. Induced innovation in agricultural development. Discussion Paper No. 3, Center for Economics Research, Department of Economics, University of Minnesota, Minneapolis.

Huang CJ, Huang T & Liu N, 2014. A new approach to estimating the metafrontier production function based on a stochastic frontier framework. Journal of Productivity Analysis 42(3): 241–54.

Jondrow J, Knox Lovell CA, Materov IS & Schmidt P, 1982. On the estimation of technical inefficiency in the stochastic frontier production function model. Journal of Econometrics 19(2–3): 233–8. https://doi.org/10.1016/0304-4076(82)90004-5

Khan H & Saeed I, 2011. Measurement of technical, allocative and economic efficiency of tomato farms in northern Pakistan. Proceedings of the International Conference on Management, Economics and Social Sciences (ICMESS 2011), 23–24 December, Bangkok, Thailand.

Kinkingninhoun-Mêgagbé FM, Diagne A, Simtowe F, Agboh-Noameshine AR & Adégbola PY, 2010. Gender discrimination and its impact on income, productivity, and technical efficiency: Evidence from Benin. Agriculture and Human Values 27: 57–69. https://doi.org/10.1007/s10460-008-9170-9

Kumbhakar SC & Lovell CAK, 2000. Stochastic frontier analysis. Cambridge: Cambridge University Press.

Lah MK, Akaba S, Bosompem M & Ntifo-Siaw E, 2018. Public and private extension services delivery to cassava farmers in Sanniquellie and Saclepea Mah Districts in Nimba County, Liberia. Journal of Sustainable Development in Africa 20(1): 64–86.

Lebot V, 2009. Tropical root and tuber crops: Cassava, sweet potato, yams and aroids. Crop production science in horticulture Series 17. Wallingford, Oxfordshire: CAB International.

LISGIS-RL, 2017. Household income and expenditure survey 2016: Statistical abstract. Monrovia, Liberia: Liberia Institute of Statistics & Geo-Information Services.

Maina FW, 2018. Assessing the economic efficiency of milk production among small-scale dairy farmers in Mukurweini sub-county, Nyeri County, Kenya. Master's thesis, University of Nairobi, Kenya.

Ministry of Agriculture, 2008. Food and agriculture policy and strategy: "From subsistence to sufficiency". Monrovia, Liberia: Ministry of Agriculture, Republic of Liberia. Available at https://www.gafspfund.org/sites/default/files/inline-files/Liberia_5_of_7_FAPS_Food_Agriculture_Strategy_0.pdf

Nginyangi JM, 2011. Economic efficiency of smallholder coffee production in Mathira District, Kenya. Master's thesis, University of Nairobi, Kenya.

Nweke FI, Spencer DSC & Lynam JK, 2002. The cassava transformation. Africa's best kept secret. East Lansing MI: Michigan State University Press.

O'Donnell CJ, Rao DSP & Battese GE, 2008. Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. Empirical Economics 34: 231–55. https://doi.org/10.1007/s00181-007-0119-4

Ogunleye AS, Adeyemo R, Bamireand AS & Binuiomote SO, 2014. Cassava production and technical efficiency in Ayedaade local government area of Osun State, Nigeria. Elixir Agriculture 71: 24465–8.

Rapsomanikis G, 2015. The economic lives of smallholder farmers An analysis based on household data from nine countries. Rome: FAO.

Tauer L, 1995. Age and farmer productivity. Review of Agricultural Economics 17(1): 63–9. Available at https://www.jstor.org/stable/1349655

Twyman J, Muriel J & García MA, 2015. Identifying women farmers: Informal gender norms as institutional barriers to recognizing women's contributions to agriculture. Journal of Gender, Agriculture and Food Security 1(2): 1–17.

Udry C, Hoddinott J, Alderman H & Haddad L, 1995. Gender differentials in farm productivity: Implications for household efficiency and agricultural policy. Food Policy 20(5): 407–23.

Ville S, Po A, Tsun JY, Sen A, Bui A & Melgar-Quiñonez H, 2019. Food security and the Food Insecurity Experience Scale (FIES): Ensuring progress by 2030. Food Security 11(3): 483–91. https://doi.org/10.1007/s12571-019-00936-9

White H, 1982. Maximum likelihood estimation of misspecified models. Econometrica 50(1): 1–25. https://doi.org/10.2307/1912526

Zinnah MM, 2016. Liberia agriculture transformation agenda: Six agro-clusters identified in Liberia. Monrovia, Liberia: Ministry of Agriculture.