Measuring efficiencies and slack in the production of indigenous vegetables in Southwestern, Nigeria

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Abstract:

The production of indigenous vegetables is a multiple input-output context that is constrained by both managerial deficiencies and diseconomies of scale. The study aimed to identify viable performance improving strategies by highlighting the technical and scale efficiencies, as well as slack values, of the 360 indigenous vegetable farms in Nigeria and the socioeconomic factors influencing them. The novelty of this study lies in the application of the Simar Wilson's double bootstrap technique in the analysis of efficiency, and the non-oriented and non-radial slack-based model. The study showed that a substantial efficiency gap existed in the production of indigenous vegetable at an average technical and scale efficiencies of 58% and 51% respectively. It found that indigeneity of the farmer and distance to the nearest extension service potentially affected both efficiencies. However, gender of the farmer and years of formal education specifically influenced technical efficiency, while, cost of planting materials, quantity of inorganic fertilizer applied, secondary occupation and land size significantly affected scale efficiency. The study concludes that possible input adjustment and output augmentation needs to be made by inefficient farms to enhance performance. A repurposed extension advisory services might be an important vehicle to mitigate adverse effects of socioeconomic factors on efficiencies.

Keywords

Simar Wilson's double bootstrap technique, slack-based model, technical efficiency, scale efficiency, indigenous vegetables.

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1.0 INTRODUCTION

Indigenous vegetables are intricately linked with reduction of hidden hunger of malnutrition. They are cheap and affordable source of proteins and vitamins especially in places and times when other sources of nutrient proved prohibitive for the Nigerian populace. Indigenous vegetable production offers means of livelihood to resource-poor farmers, many of whom are women. In Nigeria, low productivity plague agricultural performance, including indigenous vegetable production. Improvement in the relative performance of the process of transforming agricultural input to indigenous vegetable output has implication for significant resource-saving for the resource-poor farmers. Greater efficiency in resource use could increase productivity and enhance producers' competitiveness as well as the chance of survival of the farm. The identification of the factors influencing the efficiency of production of indigenous vegetables are prerequisite for intervention in the sector. The assessment of potential scope for inputs reduction as well as outputs augmentation could provide targeted adjusted that can be employed by the producers.

Shortfalls in yields relative to best practice are commonly influenced by a complex mix of relationship that is not limited to deficiencies in the management practices of farmers but is also attributed to operational, socio-economic and institutional constraints. Vegetable production is labour intensive and producers enhance productivity by hiring labour (Nwauwa and Omonona 2010). Farm size, innovative management practices in the use of seed and seedling (Ajekiigbe, Ayanwale, Oyedele, & Adebooye, (2017); Ogunmodede & Awotide, (2020)), ploughing (Girei and Dire 2013), and access to credit (Nwauwa and Omonona 2010) could extend efficiency frontier of indigenous vegetable production. However, many farm activities fall short of best practice.

Inadequate know-how of optimal fertilizer (Etim & Udoh, (2014); Tsoho & Salau, (2012) and pesticides regimes (Ogunmodede and Awotide 2020) fueled inefficiency. Access to manure offsets fertilizer cost and increased productivity (Etim and Udoh, 2014). Irrigation could have a positive (Tsoho et al. 2012) as well as negative effect (Shuaibu and Mohammed, 2018) on efficiency of dry season indigenous vegetable production even in low-laying fadama areas.

Large farming households exert significant pressure on the limited funds available for farm investments because of the need to spend money on household purchases. Unavailability of household members as a result of schooling and/or other non-farm activities worsen the problems of labour shortage. Problem of acquisition and utilization of innovation such as mechanization is not only compounded by the endemic poverty of the resource-poor farmers but also by lack of basic education, small plot size and aged farm labour ((Oladeji et al., (2017); Ogunmodede & Awotide, (2020)). More experienced and older farmers have less flexibility in letting go of their traditional practices to pave way for novel and more efficient ideas (Ibrahim and Omotesho 2013): (Nwauwa and Omonona 2010)**.** Attainment of higher education negatively influence efficiency by shifting focus of farmers from production towards competing off-farm economic endeavours (Etim and Udoh, 2014). Dossah & Mohammed (2016) demonstrates that, except for agrochemicals, the effect of land, seed, fertilizer, and irrigation water on efficiency of indigenous vegetable production were the same on both male and female farmers.

Despite the preponderance of these outlined policy variables in the literature, these studies have limitation for several reasons. First, these studies are either dated ((Nwauwa & Omonona, 2010), restricted to a single state (Oladeji et al., (2017) or focused on regions other than the Southwestern part of Nigeria ((Dossah & Mohammed, (2016); Etim and Udoh, (2014); Ibrahim & Omotesho, (2013); Nwauwa & Omonona, (2010). Second, efficiency is caused by both misallocation of resources and/or failure to take advantage of economies of scale. Differences in resource endowments and managerial abilities influence both technical and scale efficiencies. Most of the studies failed to highlight scale and slack effects in the smallholder production of indigenous vegetables.

Though, the farmers under consideration focused solely on the production of indigenous vegetables, they still cultivated multiple indigenous vegetables under various intercrop situations. Separation of relative contribution of various inputs to different vegetable outputs becomes difficult because of the synergy that exists among the production activities of the indigenous vegetables and their competition for available farm household resources. In literature, the most common approach to this problem is to coalesce the output level of different vegetables into a single composite index. This is then incorporated into parametric Stochastic Frontier Analysis (SFA). The appeal of this technique is in the "clearly defined market prices of the outputs" (Alexander et al. 2018), however, it fails to accurately mirror the production scenarios on the farm. This technique might yield useful information about production's performance but its inability to account for the operational complexity involving multiple inputs/outputs setting of indigenous production operations pose a significant problem. For instance, the interpretation of efficiency measures from such analysis as indicators of overall performance could engender a misleading and less than informed decisions and policy implications. Additional information required for recommendation for possible inputs and outputs adjustment is usually lacking in SFA since it neglects the slacks in the evaluation of efficiencies

Despite this, SFA is by far the most common tool employed in the assessment of efficiency of the indigenous vegetable production in Nigeria because of its parametric nature. SFA depends on the specification of a production function in a frontier approach that assumes a boundary, deviations from which is accounted for by inefficiency. The most commonly expressed functional forms in the study of indigenous vegetable production are linear (Omotesho et al., 2016), translog (Ajekiigbe et al. 2017), Cobb-Douglas production function (Tsoho et al. 2012) (Sanusi, Ashaolu, Akogun & Ayinde, 2015), (Dossah and Mohammed 2016); Oladeji et al., 2017). Though SFA differentiates random shocks from the effect of inefficiency, it is limited by the need for a strong assumption on the distribution of stochastic error term. Misspecification of functional form could potentially render the analysis statistically invalid. Some of the studies cited above relied on the test for the best fit production function to potentially reduce the challenge of misspecification (Ehlers, 2011). Johnes, (2006) argued that no theoretical basis exists for the specified distributional form imposed on the residual attributed to technical inefficiency. In addition, SFA lacks the flexibility to accommodate complex production forms involving multiple input and output because of the problem of endogeneity ((Berkhout et al. 2010). The stochastic distance function developed by Fare et al. (1993) and Stochastic Ray Frontier Model specified by Lothgren (1997) attempted to overcome the problem of multiproduct technology. However, these techniques suffer from regressor endogeneity, estimator inconsistency, input-output separability, linear homogeneity in outputs and biasedness ((Zhang, 2012)

The appropriate analysis of productive efficiency should consider all outputs and production inputs in a multi-input/output, multi-output framework for each DMU ((Abatania et al., 2012). Non-parametric DEA approach addressed the short comings of the SFA by incorporating multiple input and output without assuming specification of functional form; or behavioural objectives of cost minimization or profit maximization (Johnes 2006); or judgement on the knowledge of input and output prices (Ibrahim and Omotesho, (2013)). In addition, DEA provides opportunity for choice of CRS and VRS; and scale efficiency analysis. Third, DEA helps to identify the DMU with the most efficient reference set relative to others whose management practice could be followed to improve their efficiency (Abramo & D'Angelo, 2014). Despite the advantages attributed to the DEA technique, the application of the methodology has failed to draw the attention of the research community in the study of indigenous leafy vegetable in Nigeria. One of the reasons for this scarcity might have arose because of inability of DEA to differentiate between deviation from the frontier caused by inefficiency in the management of indigenous vegetable production and those caused by measurement error or other stochastic variation. This limitation implies that input and output variable were treated as fixed rather than random values. In addition, there is uncertainty in the validity of the statistical estimate derived from DEA analysis because of upward biasedness and serial correlation of the two-stage procedure.

The extension proposed by (Simar & Wilson, 2000) provided robust solutions to the shortcomings found in the DEA. They developed a double bootstrap procedure for defining a data generating process that creates a pseudo-replicate data set. This computer-based method tests the reliability of a data set by describing a statistical model consistent with the approximation of the asymptotic distribution. It estimated efficiency scores while simultaneously producing standard errors and confidence intervals for these efficiency scores. The technical details of the bootstrap procedure are discussed extensively in Simar and Wilson (2000 and 2007) and the subsequent STATA modules used for the analysis benefitted from them. This analysis employed the command introduced by Badunenko and Tauchmann (2019). The scale analysis is obtained from the non-parametric test of return to scale command by Badunenko and Mozharovskyi (2016). The most current measure of the depth of inefficiency represented by the slack was proposed by Tone (2001) in its Slack-Based Measure (SBM) of efficiency. This measure directly accounts for the input excess and output shortfall. The slack based efficiency module of Du (2019) in STATA 16 utilised for this study was developed from the works of Tone (2001)

To the best of our knowledge, this study is the first to apply the double bootstrapping, the scale analysis and the slack effect in the context of indigenous vegetable production efficiency in Nigeria. Another novelty lies in the application of non-radial and non-oriented slack-based model in the evaluation of efficiency in this subsector. From the foregoing, this paper contributes to the body of literature on indigenous vegetable production by conducting multiple input/output efficiency analyses of indigenous vegetable production in Nigeria. This study goes beyond the assessment of technical and scale efficiencies to also examined how socioeconomic variables might impact these efficiencies. The study also investigates extent of slack across scale with a view to identify viable performance improvement strategies.

2.0 Methodological approach

The efficiency analysis of the indigenous vegetable production is built primarily on four basic elements. These are the Decision-Making Unit (DMU), the set of input factors, outputs, the linear programming mathematical function describing the process of transforming inputs to outputs. In the study, each of the indigenous vegetable producer represents a decision-making unit of observation. Though dated, the existing convention on the number of respondents indicated that the DMU should be three times the number of factor inputs and outputs (320>3(5+4)) (Raab and Lichty, 2002) or should not be less than the product of the number of outputs and inputs (320> (5*4) (Boussofiane and Dyson,1991). To estimate the production frontier, the study utilised the traditional input employed on the fields. These are; - (i) labour; measured by mandays, (ii) inorganic fertilizer; measured by kilogram, (iii) organic fertilizer; measured in kilogram (iv) agrochemical; in litres, (v) land size; measured in hectares. The outputs are *Telfairia occidentalis*

Hook f, *Amaranthus cruentus* L., *Solanum macrocapon* L., *Vernonia Amygdalina* Del. All were measured in kilogram.

Farrell (1957), first proposed the production efficiency. However, Charnes, Cooper and Rhodes (1978) later introduced the term, data envelopment analysis (DEA) to describe a mathematical programming approach applied to the construction and measurement of production frontiers. Their model, named CCR relied on the assumption of constant return to scale (CRS) and assumed an input orientation. This measures the overall technical efficiency as a single index for each DMU. The overall technical efficiency is a combination of pure technical efficiency and scale efficiency. The CRS assumption is only appropriate when all DMUs are operating at an optimal scale. However, factors like missing or dysfunctional factor and product markets may restrict a DMU from attaining optimal scale. Hence, the assumption of CRS would mix up measures of technical efficiency (TE) with scale efficiencies (SE). However, the analysis of variable return to scale would provide this distinction. The assumption of variable returns to scale (VRS) was first introduced by Banker, Charnes and Cooper (1984), in a model named the BCC, to measure the pure technical efficiency. Scale efficiency is obtained by dividing the overall efficiency of the CCR by the pure efficiency of the BCC.

In this study, an input-oriented variable returns to scale, technically efficient (TE) DEA index was estimated because of rational and theoretical implications. More often than not, input resources are usually the primary decision variables in indigenous vegetable production because one of the most important emphasis is on cost minimization. The producers have less control over output which might be subjected to the vagaries of socio-environmental factors such as missing or dysfunctional market situation, erratic weather and diseases, thus, prevent them from operating at an optimal scale characterised by constant returns to scale. In addition, the respondents are heterogenous in decision-making about production activities.

In the VRS analysis, the input-based Farrell and the Russell efficiency measures were analysed. Farrell measures of technical efficiency estimated radial contractions in an isoquant enveloping all variable production factors necessary to achieve such efficiency in an equiproportionate manner. Hence, this restrictive input requirement set ignores the existence of slack associated with the projected points on the boundary of the technology which may account for additional sources of technical efficiency. Producers often bring certain input into use more intensively than others with corresponding varying level of input use efficiency, hence, there may be trade-offs in input use that may not be clearly detectable by using the radial efficiency measures alone. Russell non-radial technique provides a more flexible approach. Input-based nonradial efficiency measure allows for non-proportional/different reductions in each positive input by shrinking an input vector all the way back to the efficient subset in a DEA analysis. Output-based nonradial analysis reveals the level of output that needs to be augmented to reach the production frontier. Hence, this study utilized the non-oriented and non-radial method in its slack analysis.

2.1 Technical efficiency model

DEA is a linear programming method which uses either minimization or maximization technique. The study employs the minimization formulation because of its mathematical tractability (Coelli et al., 2005) that adapted it to the cost minimization goals of the farmers.

Following (Karimov, Awotide, and Amos 2014), the study considered *n* sample of DMU_0 (where $DMU_0 = 1, 2, \ldots, 360$), which produce *s* output γ_{no} (r=1,2,…,4) by utilizing *m* inputs, x_{no} , (i=1, 2,…,5). The piece-wise linear technology of the production possibility set each farm evaluated is

P= $\left\{(y_{r_o}, x_{i_o}) \mid x_{i_o} \geq \sum_{n=1}^{N} z_n \ x_i \ , y_{r_o} \leq \ \sum_{n=1}^{N} z_n \ y_r, \sum_{n=1}^{N} z_n = 1, z \in R_{+}^{N}\right\}$ ………….(1)

Where z= $(z_1, \dots, z_1)$ is the intensity vector with elements indicate the intensity with which each farm's production plan is taken into account in the construction of the technology frontier. The equation above indicates that a farm's production plan is a subset of the production possibilities set, if and only if, $(x_i, y_r) \in P$. Then, DEA score of each firm is calculated by solving the input-oriented linear programming problem below.

Objective function of the input-based radial technical efficiency is written as follows

$\underset{(\theta,\gamma)}{Min} \theta$,

Subject to

$\sum_{j=1}^{n} \lambda_j \, \gamma_{rj} \geq \gamma_{ro}$, (r=1,…,4): Output

$\sum_{j=1}^{n} \lambda_j \, x_{ij} \geq \theta_o \ \ \mathrm{x}_{io}$, (i=1,…,5): variable input

$\sum_{j=1}^{n} \lambda_j$ =1 λ_j ≥0 , (j=1,…,360)

The convexity constraint of the variable return to scale is

$\sum_{j=1}^{n} \lambda_j$ =1

λ_j ≥0 , (j=1,…,360)

While,

The objective function of the input-based non-radial technical efficiency is written as

$$\underset{(\theta_{,i},\gamma)}{Min} \sum_{i=I}^{I} \theta_{,i}$$

Subject to

$\sum_{j=1}^{n} \lambda_j \, \gamma_{rj} \geq \gamma_{ro}$, (r=1,…,4)

$\sum_{j=1}^{n} \lambda_j \, x_{ij} \geq \theta_o \ \ \mathrm{x}_{io}$, (i=1,…,5)

$\sum_{j=1}^{n} \lambda_j$ =1 λ_j ≥0 , (j=1,…,360)

The convexity constraint of the variable return to scale is

$\sum_{j=1}^{n} \lambda_j$ =1, λ_j ≥0 , (j=1,…,360)

In Equation (1), where θ stands for the efficiency score for the *i*th farm x_{io} and γ_{ro} are, respectively, the *i*th input and *r*th output for a DMU*o* under evaluation, respectively. Solving that model *n* times results in optimal values of the objective function and the elements of intensity variables vector λ for each farm. For the DMU*o* the optimal value $\theta{*}o$ measures the maximal proportional input reduction without altering the level of outputs. The vector λj indicates participation of each considered farm in the construction of the virtual reference farm that the DMU*o* is compared with. The value of θ ranges from 0 to 1 where 1 indicates a technically efficient DMU operating on the efficient frontier. Values of θ less than 1 operate below the efficient frontier.

The analysis followed the two-stage approach propose by (Simar & Wilson, 2007). Formally, the model is

$\widetilde{TE} \approx a + Z_j\delta + \varepsilon_{j,\ j = 1, \ldots, n,}$

Where the assumption is that the distribution is normal truncated with zero mean (before truncation), unknown variance, and (left) truncation point $\varepsilon_{j\sim N}$ $(\delta, \delta^2{}_\varepsilon)$ such that ε_j is restricted by the condition $\varepsilon_{j\ \geq\ 1\text{-}a\text{-}}Z_j\delta$, j=1,…,n. This is estimated by maximizing the corresponding likelihood function, with respect to $(\delta, \delta^2{}_\varepsilon)$. The parametric bootstrap for utilized to construct the bootstrap confidence intervals for the estimates of parameters $(\delta, \delta^2{}_\varepsilon)$ which incorporates information on the parametric structure and distributional assumption.

2.2 Scale efficiency model

The study is also interested in the economies of scale of the indigenous vegetable farms, hence it estimated the scale efficiency using,

$$SE = \frac{TE_{CRS}}{TE_{VRS}} \quad ,$$

Where, SE is the scale efficiency, TE_{CRS} is the technical efficiency under constant return to scale, while TE_{VRS} is the technical return to scale under variable return to scale.

When

SE=1, economies of scale is deemed efficient, conversely it is considered inefficient when SE < 1.

To assess SE at decreasing (DRS) or increasing returns to scale (IRS), TE under non-increasing return to scale (NIRS) must be calculated. This is calculated by changing the convexity restriction in Equation (1) to $\sum_{j=1}^{n} \lambda_j$ =1, λ_j ≤0 , (j=1,…,360).

Such that if SE<1 and VRS≠NIRS, or $\frac{TE_{CRS}}{TE_{VRS}}$ < 1 and $\frac{TE_{CRS}}{TE_{NIRTS}}$ = 1 , the farm is said operating under IRS.

If SE<1 and VRS=NIRS, or $\frac{TE_{CRS}}{TE_{VRS}}$ < 1 and $\frac{TE_{CRS}}{TE_{NIRTS}}$ =< 1, farm is said operating under DRS.

The most productive scale size occurs when TE_{CRS} = TE_{VRS} = TE_{NIRS}.

However, the most productive scale size occurs under two conditions.

The first condition when the producers are both technically and scale efficient.

TE_{CRS} = TE_{VRS} = TE_{NIRS} =1

This occurs at the constant return to scale. The second condition entails technical inefficient but are scale efficient. TE_{CRS} = TE_{VRS} = TE_{NIRS} < 1.

2.3 Slack-based efficiency model

The technical and scale efficiency models specified are based on the CCR model (Charnes et al., 1978) constant returns to scale (CRS) and BCC model (Banker et al., 1984) variable returns to scale (VRS) propositions. These models neglect the slacks in the evaluation of efficiencies. The slacks can be computed using the SBM model which is non-radial and non-oriented DEA model (Tone, 2001). The advantage of a non-oriented model is that it captures the desire to improve both inputs and outputs simultaneously. Tone (2001) proposes a slack-based measure of efficiency (SBM model), based on the assumption that data set is positive, i.e. X > 0 , Y > 0, S_r^+ and S_i^- indicating non-negativity of these variables. Given the DMU_q with the input and output matrices X = (x_{iq}) ∈ R^{mxn} and Y = (y_{rq}) ∈ R^{sxn}, respectively. The slacks S^+ ∈ R^s and $S^- \in R^m$ indicate the input excess and output shortfall of this expression. The production possibility set *P* is defined as

P = $\{(x, y)|x \geq X\lambda, y \ \leq Y\lambda, \lambda \geq 0\}$

In an effort to estimate the efficiency of DMU_q (x_{iq}, y_{rq}), Tone (2001) formulated the following minimization program:

Minimize $\frac{1-\frac{1}{M}\sum_{i=1}^{m}(S_i^-/x_{iq})}{1+\frac{1}{S}\sum_{r=1}^{S}(S_r^+/y_{rq})}$

Subject to $x_{iq} = \sum_{j=1}^{n} x_{ij}\,\lambda_j \ + \ S_i^-$ i = 1, 2,…, m

$y_{rq} = \sum_{j=1}^{n} y_{rj}\,\lambda_j \ + \ S_r^+$ r = 1, 2,…, s

$\lambda_j\,, S_r^+, S_i^- \ \geq 0$

$= \sum_{j=1}^{n} \lambda_j = 1$

Where y_{rq} are the produced amounts of r^{th} output (*r=1,2,…,s*) for DMU_q, x_{iq} are the consumed amounts of i^{th} input for DMU_j (*j=1,2,…,n*), S_i^- and S_r^+ are the input and output slacks, λ_j is the weight assigned to the DMU_j. An agricultural sector is fully SBM-efficient if p^*=1 and all slack variables are equal to zero, i. e. there is no input excess and no output shortfalls in any optimal solution. If the slack variables are not equal to zero and p^*<1, it is necessary to make non-radial shift expressed by slack variables to achieve efficiency.

2.4 Data

The sample used for this study is drawn from the population of indigenous vegetable farmers in Oyo, Osun, Ogun and Lagos states in the Southwestern part of Nigeria. Four local governments were purposively selected from each state based on their status as the hub of indigenous vegetable production in the area. Four communities were selected from each of the Local government area. In these communities, most indigenous vegetable farmers focused solely on the production of these vegetables for the market. Twenty-five respondents were selected randomly from each of the communities to give a total of 100 respondents in each state and 400 respondents altogether. Twenty-five of the respondents were found to have cassava and maize based indigenous vegetable production. Ten respondents had resorted into hiring out their labour and primary wholesale activities. Five questionnaires were incomplete. In all, forty questionnaires were removed to retain a total of 360 respondents. Primary data was collected with the aid of structured questionnaire administered by trained postgraduate students of agricultural economics and extension. Information collected included the socioeconomic variables, input factors and level of outputs. The data was analysed using Stata 16.

3.0 Results and Discussions

3.1 Descriptive characteristics of the outputs, inputs and the socioeconomic variables.

Table 1 indicates that Telfairia had the highest production volume of about 3.5million kilogram and an average of 3 hundred thousand kilogram. This is followed by Amaranthus with a maximum volume of about 8 hundred thousand and an average volume of a hundred and fifteen thousand kilogram. Igbozulike (2015) and Arowosegbe, Olainpekun, and Adeloye, (2018) reported that Telfaria and Amaranth was the most important and second most important vegetables in Southwestern Nigeria. Solanum and Vernonia had an average of 75 thousand and 60 thousand kilogram of output respectively. The producers cultivated on average 0.36 hectares of land, engaged 99 hours of mandays through the use of family and/or hired labour, utilized 85 kilogram and 98 kilogram of inorganic and organic fertilizer respectively, and about 4 litres of agrochemicals. They spent about #22,000 on planting material and hardly ever access credit facilities (19%). More than half (57%) of the respondents were male, originated from regions other than the Southwestern part of Nigeria and having indigenous vegetable production (56%) as their only occupation with no other secondary occupation. They had an average of 4 dependants in their households; spent an average of 9 years in school and travelled up to an average of 3 kilometres to the source of extension service. The summary statistics suggests that indigenous vegetables were important for the livelihood of the respondents given the volume of its production and the fact that vegetable production represented their only source of income. Further, quantity of inputs utilised suggested that the farmers were resources poor. The managerial abilities of the farmers were likely to be impaired by the low level of education and limited access to extension services.

Table 1 Description of the variables used in the efficiency analyses

Variable	Obs		Mean	Std. Dev.	Min	Max
OUTPUT						
A. cruentus	360	kilogram	115223.3	142156.4	120	796400
S. macrocapon	360	kilogram	74770.35	110529	100	599800
T. occidentalis	360	kilogram	301613.1	515975.2	3900	3497250
V. amygdalina	360	kilogram	60074.22	111527.9	800	461250
INPUT						
Land area	360	hectare	0.36	0.29	0.03	1.17

labour	360	manday	99.41875	58.99482	20	240
Inorganic fertilizer	360	kilogram	84.8375	58.27713	20	210
Organic manure	360	kilogram	98.30312	83.93122	20	280
Agrochemicals	360	litres	4.159375	2.962076	1	14
SOCIOECONOMICS						
Gender	360	female=0, male=1	43%, 57%		0	1
Region	360	Yes=1, No=0	43%, 57%		0	1
Years spent in school	360	years	8.515625	4.014051	0	17
Distance to the extension services	360	discrete	2.527666	4.844117	0	18
Dependants	360	discrete	3.740625	1.803403	0	10
Credit use	360	Yes=1, No=0	19%, 81%		0	1
Secondary occupation	360	Yes=1, No=0	44%, 56%		0	1
Cost of planting materials	360	Naira	21970.72	13582.37	2000	72500

Data Analysis (2018)

3.2 Technical efficiency of the respondents

Table 2 presents CRS and VRS Farrell (radial) and Russell (non-radial) technical efficiency scores. The mean overall efficiencies (CRS), which combined the pure and scale efficiencies of the radial estimate, was 48%, while its average pure technical efficiency represented by the VRS was 76%.

The 76% average efficiency score implies that these districts could become Farrell efficient by reducing all discretionary inputs by 24%. The table showed that at least 41% of the respondents operated below the pure efficiency margin. However, the Farrell efficiency score does not capture the total inefficiency scores observed because it failed to include the additional slack on input. The overestimation is corrected for by the inclusion of the slack component in the non-radial estimates.

On the average, the non-radial overall and pure technical efficiency estimates were 34% and 58% respectively. This implies the potential of 42% reduction in input to produce the same level of vegetables. The table showed that at least 46% of the farms failed to achieve this level of performance. The result indicated that the technical efficiency was significantly confounded by scale efficiency. It also revealed that the assumption of equiproportional distance of the radial analysis is likely to misrepresent the efficiency outlook of the indigenous vegetable production.

Considering the pure technical efficiency, the distribution of the efficiency scores showed that only 36% (n=129) of the farms were Farrell efficient. Further, of the 126 farms that were Farrell efficient, only 51 (about 14% of the total respondents) were Russell efficient. This means that 75 of the Farrell efficient farms overused some or all the categories of input in production as other non-efficient farms. This further highlight the appropriateness of the non-radial estimate in the efficiency analysis of the indigenous vegetable production. In general, the average technical efficiencies reported falls within the range reported by Aminu, Ayinde, & Ambali, (2013) and Sanusi et al., (2015) as obtained for regions in Southwestern part of Nigeria. Another important point that emerged from the analysis indicated that all technically efficient constant return to scale was also efficient at the variable return to scale. Given that CRS implies a proportionate increase in outputs as a result of a unit increase in output, the dominant source of efficiency for these

DMU's might be scale. Given the current operating practices, the efficiency of the CRS efficient farms remains unchanged irrespective of the scale unit operated.

Table 2 Frequency distribution of technical efficiency scores

Efficiency scores (%)	Radial				Non radial			
	CRS		VRS		CRS		VRS	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
<10.00	27.00	7.81	0.00	0.00	80.00	22.22	0.00	0.00
10.00-10.99	68.00	18.75	0.00	0.00	74.00	20.56	3.00	0.83
20.00-29.99	55.00	15.31	7.00	1.94	56.00	15.56	42.00	11.67
30.00-39.99	36.00	10.00	20.00	5.56	41.00	11.39	55.00	15.28
40.00-49.99	26.00	7.19	33.00	9.17	23.00	6.39	65.00	18.06
50.00-59.99	21.00	5.94	54.00	15.00	23.00	6.39	48.00	13.33
60.0-69.99	19.00	5.31	34.00	9.44	12.00	3.33	36.00	10.00
70.00-79.99	23.00	6.25	32.00	8.89	11.00	3.06	23.00	6.39
80.00-89.99	15.00	4.06	23.00	6.39	12.00	3.33	20.00	5.56
90.00-99.99	11.00	3.13	29.00	8.06	5.00	1.39	17.00	4.72
>99.99=100.00	59.00	16.25	129.00	35.83	23.00	6.39	51.00	14.17
Total	360.00	100.00	360.00	100.00	360.00	100.00	360.00	100.00
Mean	0.48		0.76		0.34		0.58	
Sd	0.33		0.24		0.29		0.25	

Data Analysis (2018)

3.3 Factors influencing the technical efficiency of the indigenous vegetable production.

Table 3 presents the result of the factors influencing the technical efficiency of the indigenous vegetable production. The result indicates a strong negative and statistical relationship between each of gender, indigeneity and years of formal education, while distance to the source of extension services were positively related to the efficiency of indigenous vegetable production.

The negative effect of gender signifies that female farmers tend to be more efficient than their male counterpart. This in consonant with the findings of Dossah & Mohammed (2016) but contrary to Obayelu et al., (2015). This inverse relationship might be as a result of a number of reasons. Vegetable is considered a woman's crop. Most women farmer found land clearing and preparation very laborious, hence are likely to outsource these activities which are carried out once at the very beginning of planting season depending on the usage pattern of the field. Moreover, in whatever form of farming household dynamics the vegetable production is carried out (whether on family farm or owned farm), the rest of the vegetable management practices which include planting, weeding, watering, harvesting, post-harvest handling and marketing were considered primarily women's duties. These activities are repetitive, and when performed overtime have the tendency to enhance efficiency of production of indigenous vegetables.

The significant and the negative sign of the indigeneity implies that the production activities of the farmers who were indigenes of the study area were less efficient than that of their counterparts who originated from states other than the Southwestern part of Nigeria. There was no prior expectation of the effect of regional affiliation on efficiency. Although, it is rational to envisage that indigeneity would engender discriminatory access to the resources, rights, and privileges necessary to enhancing efficiency, but this is not so in this case. Those farmers who originated from regions outside the Southwestern part of Nigeria may have brought innovative techniques imbibed from their places of origin into the production of the indigenous vegetables which results into improved productivity.

The result also revealed that the more the number of years of formal education the respondents had, the less efficient in the production of indigenous vegetables they are likely to be. This is corroborated by Aminu et al., (2013) and Ogunniyi and Oladejo, (2011) but contrary to the findings of Ibrahim & Omotesho, (2013). The negatively significance of years of formal education may imply that higher level of education offered opportunity for off-farm activities which divert much needed attention from vegetable production to non-farm economic activities.

The greater the distance to the source of extension services, the more the efficiency of production activities. The further away from extension advice, the more efficient the farms were. Conversely, the nearer, the farms, the less efficient they are likely to be. Nearness to an extension advisory service is likely to encourage frequency of extension services to farm site. Access to extension education enhances adoption and adaptation of improved best management practices and technologies (Tsoho et al. 2012). Ibrahim and Omotesho, (2013) was of the view that this is possible if the extension advisory services are tailored to farmers' needs and if the farmer appropriately utilise the advice given to them. This result showed that there exist certain complexities enhanced by distance to refute this assertion such that the efficiency of the farms increased with increase in the distance to the source of extension services. This dynamics justifies further studies. The result also indicates that age of the respondents and quantity of credit decreases efficiency but none of these variables were statistically significant.

Table 3 Factors influencing technical efficiency of indigenous vegetable production

Variables	Coef.	Std. Err.	P>z
Gender	-0.06363	0.027299	0.020**
Indigeneity	-0.14189	0.029683	0.000*
Age of the respondent	-0.00134	0.001256	0.285
Years spent in school	-0.0074	0.003411	0.030**
Distance to the source of extension	0.007088	0.002947	0.016**
Credit	-0.00218E-07	1.89E-07	0.250
Constant	0.793399	0.083148	0.000*
/sigma	0.194301	0.011357	0.000*

Data Analysis (2018)

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

3.4 Scale efficiency of the respondents

Table 4 presents the scale efficiency of the indigenous vegetable producers. An analysis of the scale of operation of the sampled farms revealed that most of them are not scale efficient. Only about 12% of the farms were scale-efficient implying that the size of operation of each individual farm in this group is optimal. Thus, increase or decrease in size would reduce efficiency. Average scale efficiency is 0.51, conversely scale inefficiency is 0.49. According to table 4, at least 45% of the farmers operated below this level of scale efficiency. Scale inefficiency may be interpreted, in this context, as inefficiency attributed to decreasing returns to scale which appear as the level of resources devoted to indigenous vegetable production is increased. Hence, on average, the scale inefficient farms could reduce their size by 49% without affecting their current output levels.

Table 4 Distribution of the scale efficiency of the indigenous vegetable production

Efficiency scores (%)	Freq.	%
>10.00	15.00	4.17
10.00-19.99	41.00	11.39
20.00-29.99	47.00	13.06
30.00-39.99	30.00	8.33
40.00-49.99	29.00	8.06
50.00-59.99	29.00	8.06
60.00-69.99	39.00	10.83
70.00-79.99	29.00	8.06
80.00-89.99	24.00	6.67
90.00-99.99	33.00	9.17
≤1	44.00	12.22
Total	360.00	100.00
Mean	0.51	
Standard Deviation	0.32	

Data Analysis (2018)

3.5 Nature of Return to Scale

Table 5 presents the nature of return to scale and the summary of the input variables under them. A decomposition of the scale efficiency estimates on the basis of the nature of returns to scale indicated that scale inefficiency arose as a result of increasing return to scale in the majority of the farms (70%). According to these findings, these farms were operating below the optimal scale and, hence, could increase farm size to reach the efficient frontier, provided that land presents an impediment to scale efficiency. About 29% of the farmers operated the constant return to scale which means that they were operating at their most productive scale and increase in input would yield the same proportionate increase in output. The constant return to scale farms were made up of farms that were scale efficient but not technically efficient (22%); and those that were both scale and technically efficient (7%). The inefficiency in the former could be attributed to managerial deficiencies in terms of improper use of resources, while in the latter changing the input level would lead to loss of efficiency. The rest (0.94%) of the farms exhibited decreasing return to scale, and hence, vegetable output in these farms would increase in smaller proportion to the input employed and producers would have to reduce their size to attain optimal scale. According to these findings, it can be assumed that variable return to scale better characterised the technical efficiency of the indigenous vegetable farms. A dated study carried out by Ibrahim & Omotesho, (2013) in fruit vegetable production found IRS to be 62%, CRS to be 22% and DRS to be 16%.

In terms of input use, the farms operating a decreasing return to scale utilized the largest quantities of the five categories of input. Increasing return to scale employed the second largest average manday of labour and kilogram of organic manure; and the least average quantity of organic fertilizer and agrochemicals. The most optimal farm in terms of technical and scale efficiency utilized the least amount of mandays and hectarage. This finding is somewhat in consonance with that of Abatania et al., (2012) in Ghana.

Table 5: Decomposition of the scale efficiency on the basis of return to scale and input utilisation

Nature of return to scale	Frequency	percentage	Mean	std	min	max
Decreasing return to scale	3	0.94				
Labour			221.33	64.38	166	292
Inorganic fertilizer			366.67	250.42	125	625
Organic manure			291.67	397.13	50	750
Agrochemicals			27.00	17.58	7	40
Landsize			1.17	0.00	1.17	1.17
Increasing return to scale	253	70.31				
Labour			99.30	60.12	3	340
Inorganic fertilizer			87.93	78.17	3	500
Organic manure			146.87	237.40	5	2000
Agrochemicals			4.02	4.56	1	56
Landsize			0.35	0.25	0.09	1.17
Scale but not technically efficient	80	22.19				
Labour			96.39	67.21	6	279
Inorganic fertilizer			133.39	153.35	13	750
Organic manure			117.99	208.67	2	1250
Agrochemicals			5.38	4.51	1	24
Landsize			0.40	0.34	0.03	1.17

Scale and technically efficient	24	6.56				
Labour			90.43	90.56	4	285
Inorganic fertilizer			109.95	138.11	8	600
Organic manure			54.67	98.92	10	375
Agrochemicals			5.52	4.90	1	20
Landsize			0.22	0.33	0.04	1.17
Total	360	100				

Data Analysis (2018)

3.6 Factor influencing scale efficiency of the indigenous vegetable producers

Table 6 presents the factors that influence scale efficiency of indigenous vegetable production. In the table, cost of planting materials, inorganic fertilizer, secondary occupation and distance to extension services were positive and significantly influenced scale efficiency. However, landsize, dependants and indigeneity negatively and significantly affected scale efficiency.

This implies that increasing the use of planting materials, mineral fertilizers, amaranth and V. amygdalina outputs and engagement in secondary occupation enhances scale efficiency. Though, significant at 10% the farther away from extension services a farm is, the more scale efficient it is. This is in consonant with Rahman and Awerije, (2015) who posited those farmers who have access to extension advice tends to overuse certain input that may contribute to inefficiency in scale of operation.

Further, the higher the number of hectareage brought into cultivation the lesser the scale efficiency. This could be attributed to the fact that when farmers expand land size, it is usually in a fragmented rather than in a contiguous manner. Another reason might indicate that the challenge to optimal scale is not caused by landsize as conventionally assumed but might be attributed to other input utilized in production. This signifies that farmer need not increase their farm size to increase scale efficiency. This is further corroborated by the negative effect of indigeneity. Being an indigene of a particular region confer discriminatory access to productive assets such as land. These facts considered in tandem highlight the fact that farmers who do not originate from the area of the study, though may have a relatively smaller sized farmlands, may be more scale efficient than the indigenes who may have access to larger farm expanse. On one hand, the former group might be hard-pressed to devise ingenuity in the management of other resources through distinct resourcefulness and creativity peculiar to their origin on the limited expanse of land at their disposal to enhance scale efficiency. Other studies Abatania et al., (2012) and Anang, et al, (2016) have explored effect regional difference (in terms of location) in efficiency of small scale farmers, however, *a priori* for the nexus between regional extraction, land size and scale efficiency revealed in this study is scarce. This requires further studies.

The negative effect of dependents on scale efficiency might be because higher number of dependents exert greater pressure on the fund available for expansion or increase investment in input on the farm. In addition, dependents demography of the family usually comprises of family members below the age of 16 years and the aged. The former may lack the requisite expertise to contribute significantly to farm operations in a manner that will enhance scale efficiency, while the latter may lack the capability to supplement farm family labour which can encourage going to scale. Engagement in secondary occupation provides additional source of income for investment, thereby leading to gains in efficiency. This is contrary to the findings of Anang et al., (2016) in Ghana who found that specialization enhances scale efficiency of farm production. Application of inorganic fertilizer has a positive influence on efficiency. According to Njeru, (2010) this is to be expected provided it is applied in recommended quantities given the soil mineral supplement demand.

Table 6: Determinants of scale efficiency of indigenous vegetable production

sefnp	Coef.	Std. Err.	P>t
Cost of planting material	0.015	0.005	0.002*
Inorganic fertilizer	3.890	1.270	0.002*
Land size	-0.166	0.050	0.001*
dependants	-0.021	0.008	0.009*
Indigeneity	-0.058	0.029	0.048**
Secondary occupation	0.093	0.029	0.001*
Distance to the extension services	0.005	0.003	0.088***
_cons	0.436	0.047	0.000

Data Analysis (2018)

3.7 Slack Analysis

Slack analysis shows insight into the magnitude of inefficiency and suggests improvement for the DMUs to be efficient. The table 7 presents the amount of excess input and output shortfall across scale that will enable DMUs to identify the best management practices for sustainable production. In the table above, the DMU's that were scale and technically efficient conformed to the a priori expectation that all the input variables were fully utilized and output variables were fully optimised. The DMUs operating decreasing return to scale had the highest excess in all input variables except labour and the highest shortfall in all the outputs except in S. macrocapon. On the average, the DMUs under this production regime should reduce investment in labour by 5.45 mandays, inorganic fertilizer by 250.16kg, organic manure by 235.48kg, agrochemicals by 12.17 litres and landsize by 0.91 hectares. These respondents optimized the production of S. macrocapon but produced insufficient output of close to 900000 kg of the other three vegetables.

Increasing return to scale showed an average highest waste in labour (34.43 mandays) and relatively higher waste in the use of inorganic fertilizer (54.95kg), organic manure (129.46kg), agrochemicals (2.19 litres) and landsize (0.24 hectares). They produced insufficient output to the tune of almost 200,000kg of A. Cruentus, S. Macrocapon and V. Amygdalina. The average shortfall in T. Occidentalis was about 580000 kg. Producers that were scale but not technically efficient overuse the second largest kilogram of inorganic fertilizer (77.55kg), number of mandays (23.03) and the land size (0.29 hectare) and the least level of organic manure (90.07kg) and agrochemicals (2 litres). The highest shortfall in output was T. Occidentalis (558228kg), followed by V. Amygdalina (253095kg), while that of A. Cruentus and S. Macrocapon were less than 125000kg each. This result implied that all the scale except the scale and technically efficient producers engaged excess resources which are highly underutilized and experience shotfall in output levels.

Table 7 Input and output slack of the indigenous vegetable production

Decreasing return to scale			
Input	Input slack	Output	Output slack (kg)

Labour (mandays)	5.45	A. cruentus	890589.56
Inorganic fertilizer (kg)	250.16	S. macrocapon	0.00
Organic manure (kg)	235.48	T. occidentalis	884365.50
Agrochemicals (litres)	12.17	V. amygdalina	880507.48
Landsize (ha)	0.91		
Increasing return to scale			
Labour (mandays)	34.43	A. cruentus	118182.97
Inorganic fertilizer (kg)	54.95	S. macrocapon	197008.86
Organic manure (kg)	129.46	T. occidentalis	581859.52
Agrochemicals (litres)	2.19	V. amygdalina	190479.61
Landsize (ha)	0.24		
Scale but not technically efficient			
Labour (mandays)	23.03	A. cruentus	114766.31
Inorganic fertilizer (kg)	77.55	S. macrocapon	124554.15
Organic manure (kg)	90.07	T. occidentalis	558228.86
Agrochemicals (litres)	2.00	V. amygdalina	253095.96
Landsize (ha)	0.29		
Scale and technically efficient			
Labour (mandays)	0.00	A. cruentus	0.00
Inorganic fertilizer (kg)	0.00	S. macrocapon	0.00
Organic manure (kg)	0.00	T. occidentalis	0.00
Agrochemicals (litres)	0.00	V. amygdalina	0.00
Landsize (ha)	0.00		

Data Analysis (2018)

CONCLUSIONS

The main objective of the study is to assess technical and scale efficiencies of indigenous vegetable farms in Southwest Nigeria as well as the factors that affect them. This is with a view to proffer performance improving solutions. The scarcity of empirical analysis of multiple input and output framework using the double bootstrapped procedure in the analysis of the efficiency of indigenous vegetable production motivated this study. The overall result showed that the producers have more room to improve efficiency given the level of existing technology. Taken into consideration the slack component arising from input combination, the farmers could reduce input utilization by 42% and still produce the same level of output. Gender, indigeneity, years of formal education, distance to the source of extension services were the factors influencing the technical efficiency of the indigenous vegetable production.

The analysis of the scale efficiency revealed an average scale efficiency of 51% with most of the farms under the increasing return to scale. Out of the 29% of the farms that operated under constant return to scale, only about 7% were both technical and scale efficient. Very few were in a decreasing return to scale operation. Cost of planting materials, inorganic fertilizer, secondary occupation and distance to extension services made positive and significantly impact on scale efficiency, while landsize, dependants and indigeneity negatively affected it. The slack analysis showed that all the producers except those that were scale and technically efficient showed significant amount of excess input utilization and deficient output production. The study concludes that most farms have not been successful in employing best-practices production methods and achieving the maximum possible output from new and existing technologies.

These findings stress the need for appropriate policy formulation and implementation that would promote mechanization of laborious and repetitive activities in the indigenous vegetable production for both gender. Most farms would benefit by becoming larger; however, farmers need to reconsider optimal input combination especially since cost of planting materials, inorganic fertilizer and land have the highest potential to improve scale efficiency. There is a need to repurpose the extension services institution to better meet the need of the farmers and mitigate the context-specific socioeconomic dynamics limiting maximum efficiency. The presence of slack variable, especially in the farms that were scale but not technically efficient calls for the facilitation of best management practices among the producers to increase the benefits derivable from indigenous vegetable production.

These findings need to be considered in light of the limitations of this study, which suggest a number of interesting research directions. Out of line with expectation, the effect of the distance to the source of extension services is found be unfavourable on both technical and scale efficiency such that the farther the distance the more efficient the farms. The nexus between regional extraction, land size and scale efficiency revealed in this study is novel. These require further studies.

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