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Research Article

DISAGGREGATED EVALUATION OF ENERGY CONSUMPTION AND GHG EMISSION IN SORGHUM PRODUCTION IN NIGER STATE OF NIGERIA

***Sadiq, M S[1&2] and Grema, I.J[3]**
[1]*Department of Agricultural Economics, SKRAU, Bikaner, India*
[2]*Department of Agricultural Economics and Extension Technology, FUT, Minna, Nigeria*
[3]*Department of Agricultural Technology, Yobe State College of Agriculture, Gujba, Nigeria*
**Author for Correspondence*

ABSTRACT
This research empirically modeled energy consumption and GHG emission reduction in sorghum production in Niger State of Nigeria, using cross sectional data collected from 90 farmers' *viz.* multi-stage sampling techniques. Efficiency of energy inputs used in sorghum production was studied; degrees of technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) were determined; wasteful uses of energy by inefficient units were assessed; energy saving of different sources was computed; effect of energy optimization on greenhouse gas (GHG) emission was investigated; and, the total amount of GHG emission of actual energy used was compared with optimum energy required using data envelopment analysis (DEA). Based on findings, it was found that 20% and 80% of sorghum producers based on BCC model were efficient and inefficient, respectively. However, the average technical, pure technical and scale efficiency scores of producers were 0.599, 0.778 and 0.77, respectively. Furthermore, it was observed that 34.15% (1009.35MJha^{-1}) of total energy input can be saved if the performance of inefficient farms rose to a high level while still maintaining the same level of yield currently achieved. The improved energy use efficiency, energy productivity, net energy, total energy output and productivity of efficient units were found to be higher than that of inefficient units' by 39.47%, 38.46%, 20.95%, 9.88% and 9.88%, respectively, using energy optimization technique. Furthermore, the greenhouse gas emission in efficient units was less than that of inefficient units by about 20.01% which translate into the value of 11.83KgCO$_{2eq}$ha^{-1}. However, nitrogen fertilizer had the highest difference of greenhouse gas emissions between efficient and inefficient unit in sorghum production. Based on these, it is recommended that policies should emphasize on development of new technologies to substitute agrochemical inputs with renewable energy sources aiming efficient use of energy and lowering the environmental footprints. Also, the use of stereotype fertilizer should be discouraged, and if possible policy banning it should be enacted.

Keywords: *Energy, GHG Emission, Efficient vs. Inefficient, Sorghum, Nigeria*

INTRODUCTION

Climate change also known as global warming refers to the rate in average surface temperature on the earth; while change in the weather may occur suddenly and noticeably, changes in the climate take a long time, and are thereof less obvious. There have been changes in the earth's climate and all forms adapted naturally to this change. However, in the last 150-200 years climate change has been taking place too rapidly, such that certain plant and animal species find it hard to adopt. Though, human activities are said to be responsible for the speed at which climate change has been taking place. Agricultural sector is a driving force in the gas emissions and land use effects thought to cause climate change. In addition to being a significant user of land and consumer of fossil fuel, agriculture contributes directly to greenhouse gas emissions through practices such as arable crop production and livestock rising. According to the Intergovernmental Panel on Climate Change (IPCC, 2007), the three main causes of increase in GHG observed over the past 250 years, have been fossil fuels, land use and agriculture. As the global awareness and effects of climate change increases, so is the fear that crop production which has become Nigerian agricultural mainstay is at risk. Fear is rife that agricultural sector is seriously under threat by climate change which is affecting crop production. Many studies, Fischer *et al.,* (2002), Sathaye *et al.,* (2006), Singh and Pal, (2010) have suggested that rising temperature could be harmful to farms around the world, although there are plenty of uncertainty about how bad things will get and which food supplies we should worry about most. The consistent negative impact from increasing temperature warrant critical needed investment in climate change adaptation strategies to counteract the adverse effects of rising temperature on global crop production, including genetic improvement and management adjustments. It is a known fact that global warming and climate change have emerged as a serious threats to the sustainability of natural environment, farming, as well as all forms of life. And to meet this challenge, development programmes must have built-in provision for mitigating the impact of global warming and climate change. The policy makers need comprehensive knowledge and understanding of the implication of global warming and climate change, so that programmes can be oriented accordingly. However, this current research explore on mitigation strategies of GHG emission in Nigerian agriculture which contribute to global warming and climate change, with special reference to arable crop production due to dearth of consequential empirical information, because literature review showed only few empirical studies which adopted consequential methodology (non-parametric) e.g Khoshnevisan *et al.,* (2013), Nabavi-Pelesaraei *et al.,* (2014), Sadiq *et al.,* (2016a), Sadiq *et al.,* (2016b). Also, effective energy use and sustainability in agricultural production are significantly correlated and literature is repeated with reports focused on energy consumption in agricultural production. Safa and Samarasinghe (2011) as cited by Khoshnevisan *et al.,* (2015) reported that energy modeling is an interesting subject for engineers and scientists who are concerned with energy production, consumption and related environmental impacts.

MATERIALS AND METHODS

Research Methodology

This study was conducted in Niger State of Nigeria. The state is located in the north-central part of Nigeria, lying between longitude $3^0\ 30^1$ and $7^0\ 20^1$ east of the Greenwich Meridian and latitude $8^0\ 20^1$ and $11^0\ 30^1$ north of the equator (Sadiq and Yakasai, 2012); with approximately 80,000 square kilometre landmass having varying physical features like hills, lowland and rivers; enjoys luxuriant vegetation with vast northern guinea savannah found in the north while the fringe (southern guinea savannah) in the southern part of the state (Sadiq and Isah, 2015); annual precipitation is between 1100mm and 1600mm with average monthly temperature hovering around 23˚C to 37˚C (Sadiq, 2016). The inhabitants are predominantly peasant farmers cultivating mainly food crops such as yam, cassava, maize, rice and sorghum for family consumption and market (Sadiq, 2014). A multi-stage sampling technique was relied upon to select 90 sorghum farmers who were spread over 3 agricultural zones of the state. Stage wise selection are: purposive selection of all the three (3) agricultural zones because the crop is cultivated across the state; followed by purposive selection of one (1) LGA from each zone based on preponderance of sorghum producers; then random selection of three (3) villages from each chosen LGA; and random selection of ten (10) producers from each chosen village, thus, given a total sample size of 90 active producers. Developed structured questionnaire after been pre-tested was administered on the study's respondents on fortnight basis during 2015 cropping season to gather information on inputs-output. Collected data were analyzed using Data Envelopment Analysis model (DEA).

Table 1a: Equivalents for Various Sources of Energy

Items	Unit	Equivalent MJ	Remarks
Labour	Man-hour	1.96	
Seeds	Kg	15.2	Processed
Nitrogen	Kg	60.60	
P_2O_5	Kg	11.1	
K_2O	Kg	6.7	
Herbicides	Kg	238	
Sorghum output (seed)	Kg	14.7	

Table 1b: Amount of Inputs-Output and their Energy Equivalents for Sorghum Production

Input	Qty ha^{-1}	Equivalent MJ	Total Energy Equivalent ($MJha^{-1}$)	Percentage
Family labour	114.09	1.96	223.62	7.55
Human Labour	70.577	1.96	138.33	4.66
Improved seeds	2.799	15.2	42.55	1.42
Nitrogen	28.52	60.6	1728.28	58.43
P_2O_5	14.26	11.1	158.28	5.33
K_2O	14.26	6.7	95.54	3.21
Herbicides	14.26	238	568.82	19.42
Total input			**2955.42**	**100**
Sorghum product (seed)	814.124	14.7	11967.62	
Total output energy			**9012.20**	

Source: Field survey, 2015

Empirical Model

Data Envelopment Analysis (DEA)

Mathematically, DEA is a Linear Programming (LP)-based methodology for evaluating the relative efficiency of a set of Decision Making Units (DMUs) with multi-input and multi-output, i.e. a non-parametric data analytic technique whose domain of inquiry is a set of entities, commonly called decision-making units (DMUs), which receive multiple inputs and produce multiple outputs (Heidari *et al.*, 2012). The technique builds a linear piece-wise function from empirical observations of inputs and outputs. Unlike parametric methods, DEA does not require a function to relate inputs and outputs. The DEA envelops the data in such a way that all observed data points lie on or below the efficient frontier (Coelli, 1996). Also, it does not require any assumption on the shape of the frontier surface and it makes no assumptions concerning the internal operations of a DMU (Emrouznejad and Tavana, 2014). The efficient frontier is established by efficient units from a group of observed units. In DEA an inefficient DMU can be made efficient either by minimizing the input levels while maintaining the same level of outputs (input oriented), or, symmetrically, by maximizing the output levels while holding the inputs constant (output oriented). Since DEA was first introduced in 1978 in its present form, researchers in a number of fields have quickly recognized that it is an excellent and easily used methodology for modeling operational processes for performance evaluations. This has been accompanied by other developments (Cooper *et al.*, 2011). It means DEA is receiving increasing importance as a tool for evaluating and improving the performance of manufacturing and service operations. It has been extensively applied in performance evaluation and benchmarking of schools, hospitals, bank branches, production plants, etc. (Charnes *et al.*, 1978). Also, agricultural enterprise and its profitability rely on finite and scarce resources; therefore, the use of input-oriented DEA models is more appropriate to minimize costs and maximize profit in the production process.

Charnes *et al.*, (1984) introduced CCR model which was built on the assumption of constant returns to scale. It is also called the global efficiency model. Later, Banker *et al.*, (1984) suggested the BCC model based on variable returns to scale (VRS) and it is also called the local efficiency model. DEA models are broadly divided into two categories on the basis of orientation: input-oriented and output-oriented. Objective of input-oriented model is to minimizing inputs while maintaining the same level of outputs, whereas output-oriented model focus on increasing outputs with the same level of inputs. In this study an input-oriented (VRS) DEA model was used to determine efficient and inefficient DMUs.

Three different forms of efficiency defined by DEA are technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE). The efficiency models are given below:

Technical efficiency (TE)

TE can be defined as the ability of a DMU (e.g. a farm) to produce maximum output given a set of inputs and technology level. The TE score (θ) in the presence of multiple-input and output factor can be calculated by the ratio of sum of weighted outputs to the sum of weighted inputs or in a mathematical expression given below (Cooper *et al*., 2004):

$$\theta = \frac{U_1Y_1j + U_2Y_2j + \dots + UsYsj}{V_1X_1j + V_2X_2j + \dots + VmXmj} = \frac{\sum_{r=1}^{s} UrYrj}{\sum_{i=1}^{m} ViXij} \quad \dots\dots (1)$$

Let the DMU*j* to be evaluated on any trial be designated as DMU*o* (*o* = 1, 2 . . . *n*). To measure the relative efficiency of a DMU*o* based on a series of *n* DMUs, the model is structured as a fractional programming problem, and specified as follows (Cooper *et al.*, 2006):

$$\text{Max: } \theta = \frac{\sum_{r=1}^{s} UrYr0}{\sum_{i=1}^{m} ViXi0} \quad \dots\dots (2)$$

$$\text{Subject to: } \frac{\sum_{r=1}^{s} UrYrj}{\sum_{i=1}^{m} ViXij} \leq 1 \qquad j=1, 2 \dots\dots n$$

$Ur \geq 0, \quad Vi \geq 0$

Where, *n* is the number of DMUs in the comparison, *s* the number of outputs, *m* the number of inputs, *Ur* (*r* = 1, 2, …, *s*) the weighting of output *Yr* in the comparison, *Vi* (*i* = 1, 2, …, *m*) the weighting of input *Xi*, and *Yrj* and *Xij* represent the values of the outputs and inputs *Yj* and *Xi* for DMU*j*, respectively. Equation (2) can equivalently be written as a linear programming (LP) problem as follows:

$$\text{Max: } \theta = \sum_{r=1}^{s} UrYro \quad \dots\dots (3)$$

$$\text{Subject to: } \sum_{r=1}^{s} UrYrj - \sum_{i=1}^{m} ViXij \leq 0 \qquad J=1, 2 \dots\dots n$$

$$\sum_{i=1}^{m} UiXio = 1$$

$Ur \geq 0, Vi \geq 0$

The dual linear programming (DLP) problem is simpler to solve than Equation (3) due to fewer constraints. Mathematically, the DLP problem is written in vector–matrix notation as follows:

$$\text{Min: } \theta \dots\dots (4)$$

$$\text{Subject to: } Y\lambda \geq y0$$
$$X\lambda - \theta X0 \leq 0$$
$$\lambda \geq 0$$

Where, *Yo* is the *s* x 1 vector of the value of original outputs produced and *Xo* is the *m* x 1vector of the value of original inputs used by the o^{th} DMU. *Y* is the *s* x *n* matrix of outputs and *X* is the *m* x *n* matrix of inputs of all *n* units included in the sample. λ is a *n* x 1 vector of weights and Θ is a scalar with boundaries of one and zero which determines the technical efficiency score of each DMU. Model (4) is known as the input-oriented CCR DEA model. It assumes constant returns to scale (CRS), implying that a given increase in inputs would result in a proportionate increase in outputs.

Pure technical efficiency (PTE)

The TE derived from CCR model, comprehend both the technical and scale efficiencies. So, Banker *et al.*, (1984) developed a model in DEA, which was called BCC model to calculate the PTE of DMUs. The BCC model is provided by adding a restriction on λ (λ =1) in the model (4), resulted to no condition on the allowable returns to scale. This model assumes variable returns to scale (VRS), indicating that a change in inputs is expected to result in a disproportionate change in outputs.

Scale efficiency (SE)

SE relates to the most efficient scale of operations in the sense of maximizing the average productivity. A scale efficient farmer has the same level of technical and pure technical efficiency scores. It can be calculated as follow:

$$SE = \frac{TE}{PTE} \quad \dots\dots (5)$$

SE gives the quantitative information of scale characteristics. It is the potential productivity gained from achieving optimum size of a DMU. Using scale efficiency helps producers to find the effect of farm size on efficiency of production. Simply, it indicates that some part of inefficiency refers to inappropriate size of DMU, and if DMU moved toward the best size the overall efficiency (technical) can be improved at the same level of technologies (inputs) (Nassiri and Singh, 2009; Qasemi-Kordkheili and Nebavi-Pelesaraei, 2014). If a farm is fully efficient in both the technical and pure technical efficiency scores, it is operating at the most productive scale size. On the other hand, if a farm has high pure technical efficiency score, but a low technical efficiency score, then, it is locally efficient but not globally efficient due to its scale size, while a technical efficient farm is termed to be global efficient. Thus, it is reasonable to characterize the scale efficiency of a DMU by the ratio of the two scores (Sarica and Or, 2007).

However, scale inefficiency can be due to the existence of either IRS or DRS. A shortcoming of the SE score is that it does not indicate if a DMU is operating under IRS or DRS conditions. This problem is resolvable by solving a non-increasing returns of scale (NIRS) DEA model, which is obtained by substituting the VRS constraint of $\lambda = 1$ in the BCC model with $\lambda \leq 1$. IRS and DRS can be determined by comparing the efficiency scores obtained by the BCC and NIRS models; so that, if the two efficiency scores are equal, then DRS apply, else IRS prevail. The information on whether a farmer operates at IRS, CRS or DRS status is particularly helpful in indicating the potential redistribution of resources between the farmers, thus, enables them to achieve higher output. The results of standard DEA models divide the DMUs into two sets of efficient and inefficient units. The inefficient units can be ranked according to their efficiency scores; while, DEA lacks the capacity to discriminate between efficient units. A number of methods are in use to enhance the discriminating capacity of DEA (Adler *et al.*, 2002). In this study, in order to overcome this problem benchmarking method developed by Sexton *et al.*, (1986) were used. In the case of benchmarking method, an efficient unit which is chosen as the useful target for many inefficient DMUs and so appears frequently in the referent sets, is highly ranked.

Energy Saving Target Ratio (ESTR): Energy saving target ratio (ESTR) helps to determine the inefficiency level of energy usage, and the index used is given below:

$$\textbf{ESTR (\%)} = \frac{\text{Energy saving target} \times 100}{\text{Actual energy input}} \quad \text{……………………………………} (8)$$

ESTR represents each inefficiency level of energy consumption with its value between zero and unity. A higher ESTR implies higher energy use inefficiency, thus, a higher energy saving amount.

Coefficient of Multiple Determination (R^2)

$$\mathbf{R^2} = 1 - \frac{\sum_{i=1}^{n} (A_i - F_i)}{\sum_{i=1}^{n} A_i}$$

Where, $\mathbf{R^2}$ = coefficient of multiple determination; A_i = actual total energy input for ith farmer; and, P_i = Projected required total energy input for ith farmer.

GHG Emissions

CO_2 emission coefficients of agricultural inputs were used to quantifying GHG emissions in sorghum production (Table 2).

Table 2: GHG Emission Coefficients of Agricultural Inputs

Items	Unit	GHG Coefficient ($KgCO_2$eq. unit^{-1})
Nitrogen	Kg	1.3
P_2O_5	Kg	0.2
K_2O	Kg	0.2
Herbicides	Kg	6.3

RESULTS AND DISCUSSION

Measuring the Efficiency of Farmers

Results of farmers' efficiency score distribution obtained by application of CCR and BCC models are shown in Figure 1. Based on findings approximately 7.8 percent (7 farmers) and 20 percent (18 farmers) were identified as relative efficient farmers under CRS and VRS assumptions, respectively, while about 92.2 percent (93 farmers) and 80 percent (72 farmers) with respect to CRS and VRS were inefficient as their efficient scores were below 1. An efficiency score of less than 1 for CRS implies that a DMU did not apply the right techniques properly, while an efficiency score of less than 1 for VRS indicates that a DMU is inefficient in input use i.e. there was resource wastage. Furthermore, among the efficient farmers only 7 DMUs were identified to be fully efficient in both technical and pure technical efficiency scores, implying they are globally efficient and operated at the most productive scale size, while the remaining 11 pure technically efficient DMUs were only locally efficient, and this was due to their disadvantageous conditions of scale size. However, 61.2 percent and 26.7 percent, with respect to CRS and VRS, had their TE and PTE scores between 0.50 and 0.99. If CCR model is assumed, only 31.1 percent had an efficiency score of less or equal to 0.49; whereas, if BCC model is applied, approximately 7.8 percent had an efficiency scores of less or equal to 0.49. It is noteworthy that among the inefficient farmers, 1 DMU and 14 DMUs with respect to CRS and VRS had their TE and PTE scores between 0.90 and 0.99, meaning that these DMUs should be able to produce the same level of output using their efficiency score at their current level of energy inputs when compared to their benchmark which are constructed from the best performing DMUs with similar characteristics.

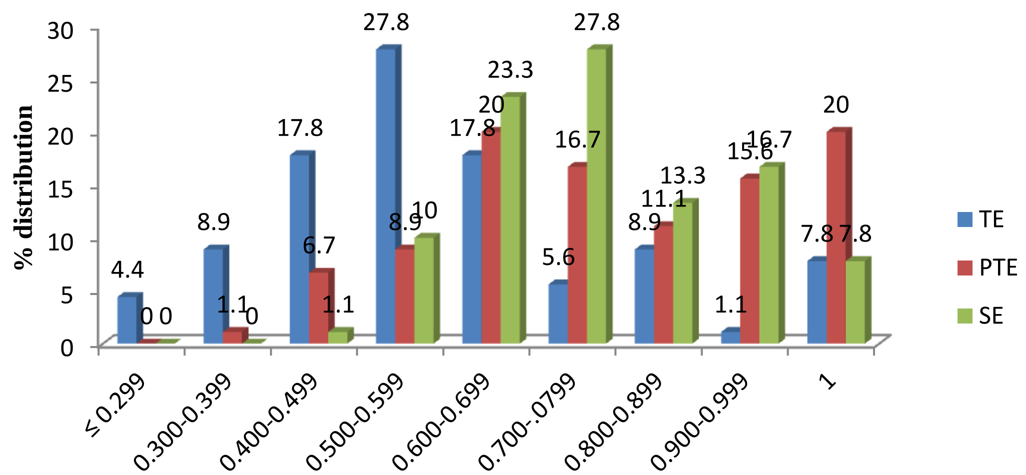


Figure 1: Percentage distribution of efficiency scores of farmers

The summarized statistics for TE, PTE and SE are given in Table 3. The mean values for TE, PTE and SE were found to be 0.599, 0.778 and 0.770, respectively, and for adjustment purpose, the average farmer(s) with respect to TE need to increase his/her technical efficiency by 40.1 percent *viz.* appropriate adoption of required techniques to be on the frontier surface; in the case of PTE, farmer(s) need to reduce energy inputs consumed by approximately 22.2 percent to be on the frontier surface; while in the case of SE, farmer(s) need to increase their scale productivity by 23 percent *viz.* right input mix to be on the frontier surface. However, the wide variation in TE scores from 0.599 – 1.00 is an indication that virtually all the farmers were not fully aware of the right production techniques or did not apply them properly. Also, relatively low average SE score indicates the disadvantageous conditions of scale size, thus, implying that if all the inefficient farmers operated at the most productive scale size, 23 percent savings in energy input use from different sources would be possible without affecting the productivity level.

Return to Scale

The BCC model includes both IRS and DRS, while NIRS model gives DRS. To determine whether a DMU has IRS or DRS, an additional test is required. The values of TE for both BCC and NIRS were calculated and their values were compared. The same values of TE for NIRS and BCC models show that the DMU has DRS, while different values imply that the farm has IRS. Results showed that DMU25, DMU56. DMU63, DMU66, DMU67, DMU68, DMU86 that were efficient under the CRS model are both technically and scale efficient (Appendix). The returns to scale estimation indicated that all the technically efficient farmers based on the CCR model were operating at CRS, showing the optimum scale of their practices and for inefficient DMUs technological change is required for considerable changes in output. Furthermore, RTS results showed that 8 DMUs operated at CRS; 1 DMU operated at DRS, while 81 DMUs were found to be operating at IRS (Table 4). Therefore, a proportionate increase in all inputs leads to more/less/constant proportionate increase in outputs; and for considerable changes in yield, technological changes in practices are required. The information on whether a farmer operates at IRS, CRS or DRS is particularly helpful in aiding potential redistribution of resources between the farmers in order to enable them achieve higher output.

Table 3: Deciles Frequency Distribution of Efficiency Scores

Efficiency Level	TE	PTE	SE
≤ 0.299	4 (4.4)	0 (0)	0 (0)
0.300-0.399	8 (8.9)	1 (1.1)	0 (0)
0.400-0.499	16 (17.8)	6 (6.7)	1(1.1)
0.500-0.599	25 (27.8)	8 (8.9)	9 (10)
0.600-0.699	16 (17.8)	18 (20.0)	21 (23.3)
0.700-0.799	5 (5.6)	15 (16.7)	25 (27.8)
0.800-0.899	8 (8.9)	10 (11.1)	12 (13.3)
0.900-0.999	1(1.1)	14 (15.6)	15 (16.7)
1.000	7 (7.8)	18 (20.0)	7 (7.8)
Total	90	90	90
Minimum	0.259	0.366	0.444
Maximum	1	1	1
Mode	1	1	1
Mean	0.599	0.778	0.770
STD	0.190	0.186	0.149

Source: Computed from EMS computer print-out
( ): percentage

Table 4: Characteristics of Farms with Respect to Return to Scale

Scale	No. of Farms	Mean Energy Output
Sub-optimal	81	11145.18
Optimal	8	20425.65
Super-optimal	1	16139.38

Source: Computed from EMS computer print-out

Ranking Analysis of Sorghum Farmers

It is worthy to note that efficient farmers obviously follow good operating practices, and identifying efficient operating practices and their dissemination will help to improve efficiency not only in the case of inefficient farmers but also for relatively efficient ones. However, among the efficient farmers, some DMUs showed better operating practices than others, as such there is need to make discrimination among the efficient farmers while seeking the best operating practices. These efficient DMUs can be selected by inefficient DMUs as best practice DMUs, making them a composite DMU instead of using a single DMU as a benchmark. In order to have the efficient farmers ranked, the number of times an efficient DMU appears in a referent set was counted (Table 5). Only efficient DMUs serve as peers for the inefficient DMUs, and in this instance DMUs 11-16, 25-53, 56-62, 63-66, 67-68, 72-74 and 19 are the efficient peers. However, DMU56 appears forty eight times in the reference set of inefficient DMUs, thus, placing it closest to the input and output levels of most of the inefficient DMUs, because it had the most optimum inputs used. Therefore, DMUs with zero peer counts are advised to emulate these best practice DMU if they their objective is to be technical and scale efficient. While the referent set is composed of the efficient units which are similar to the input and output levels of inefficient units, efficient DMUs with more appearance in referent set are known as superior unit/spark plug in the ranking. These superior units/spark plugs can be use as reference means of dissemination of farm improvement by extension delivery service agents. It is noteworthy that results of this analysis would be beneficial to inefficient farmers to manage their energy sources usage in order to attain the best performance of energy use efficiency.

Table 5: Benchmarking of Efficient DMUs

DMU (Farm)	Frequency in Referent Set	Ranking	DMU (Farm)	Frequency in Referent Set	Ranking
DMU56	48	1	DMU74	7	8
DMU25	45	2	DMU63	4	9
DMU11	43	3	DMU72	3	10
DMU67	35	4	DMU66	2	11
DMU86	19	5	DMU62	2	11
DMU53	12	6	DMU68	1	12
DMU16	11	7			

Source: Computed from EMS computer print-out

Performance Assessment of Efficient Farms Using Weight

Performance assessment can be carried out by comparing a particular system with key competitors having best performance within the same group or another group performing similar functions, and this process is called benchmarking (Jebaraj and Iniyan, 2006). Efficient DMUs can be selected by inefficient DMUs as best practice DMUs, making them a composite DMU instead of using a single DMU as a benchmark. A composite DMU is formed by multiplying the intensity vector λ in the inputs and outputs of the respective efficient DMUs. BCC is modeled by setting the convexity constraint and the summation of all intensity vectors in a benchmark DMU must be equal to 1. Results in Table 6 show the worst inefficient DMUs (DMU01 and DMU40) and the best inefficient DMUs (DMU21and DMU60). For instance, in the case of DMU01 the composite DMU that represents the best practice or reference composite benchmark DMU is formed by the combination of DMU56, DMU67 and DMU11. This means DMU01 is close to the efficient frontier segment formed by these efficient DMUs represented in the composite DMU. The selection of these efficient DMUs is made on the basis of their comparable level of inputs and output to DMU01. However, the benchmark DMU for DMU01 is expressed as 56(0.602) 67(0.197) 11(0.201), where 56, 67 and 11 are the DMU numbers while the values between the brackets are the intensity vector λ for the respective DMUs. The higher value of the intensity vector λ for DMU67 (0.472) indicates that its level of inputs and output is closer to DMU40 when compared to other DMUs in the composite set.

Table 6: Performance Assessment of Farms

DMU (Farm)	PTE Score (%)	Benchmarks
DMU01	36.6	56(0.602) 67(0.197) 11(0.201)
DMU40	40.0	67(0.472) 56(0.342) 25(0.144) 11(0.042)
DMU21	97.0	56(0.044) 25(0.837) 74(0.119)
DMU60	97.1	25(0.069) 11(0.713) 67(0.219)

Source: Computed from EMS computer print-out

Optimum Energy Requirement and Saving Energy

The optimum energy requirement and saving energy of various inputs for sorghum production using BCC model are presented in Table 7. It gives the average energy usage in optimum conditions ($MJha^{-1}$), possible energy savings and ESTR percentage for different energy sources. Results showed that the total actual energy requirement for sorghum production was 2955.42$MJha^{-1}$, and could be reduced to 1946.07$MJha^{-1}$; while, maintaining the present production level and also assuming no other constraining factors. Estimated required energy inputs from nitrogen, herbicides, family labour and P_2O_5 are 1201.53, 311.27, 134.09 and 110.03 MJha^{-1}, respectively. Moreover, required energy inputs from hired labour, K_2O and seed are 95.41, 66.41 and 27.33 MJha^{-1}, respectively.

The ESTR results showed that if all farmers operated efficiently, reduction in herbicides, family labour and seeds energy inputs, with respect, by 45.28%, 40.04% and 35.77% would have been possible without affecting the productivity level. Energy inputs *viz.* family labour, herbicides and seeds had the highest inefficiency which owed mainly to inadequate technical know-how in their application which results in excess use. High herbicides energy input percentage can be due to low literacy level of farmers which inhibit their ability to comprehend instructions on its application; poor extension service delivery and low prices of this input. Also, high percentage of family labour and seed energy inputs can be attributed to subsistence nature of farming which relies heavily on farm family labour and seeds from their previous harvests which are free and in abundance, and in most cases are not channeled into alternative purpose. Accurate management of family labour and seeds by increasing their efficiency in sorghum production and absorbing excess labour into alternative ventures, and loss reduction by improving management practices can improve energy use.

Table 7: Energy Saving (MJha^{-1}) from Different Sources

Input	Actual Energy Used (MJha^{-1})	Optimum Energy Requirement (MJha^{-1})	Energy Saving	ESTR (%)
Family labour	223.62	134.09	89.53	40.04
Human labour	138.33	95.41	42.92	31.03
Seed	42.55	27.33	15.22	35.77
Nitrogen	1728.28	1201.53	526.75	30.48
P_2O_5	158.28	110.03	48.25	30.48
K_2O	95.54	66.41	29.13	30.49
Herbicides	568.82	311.27	257.55	45.28
Total energy input	2955.42	1946.07	1009.35	34.15

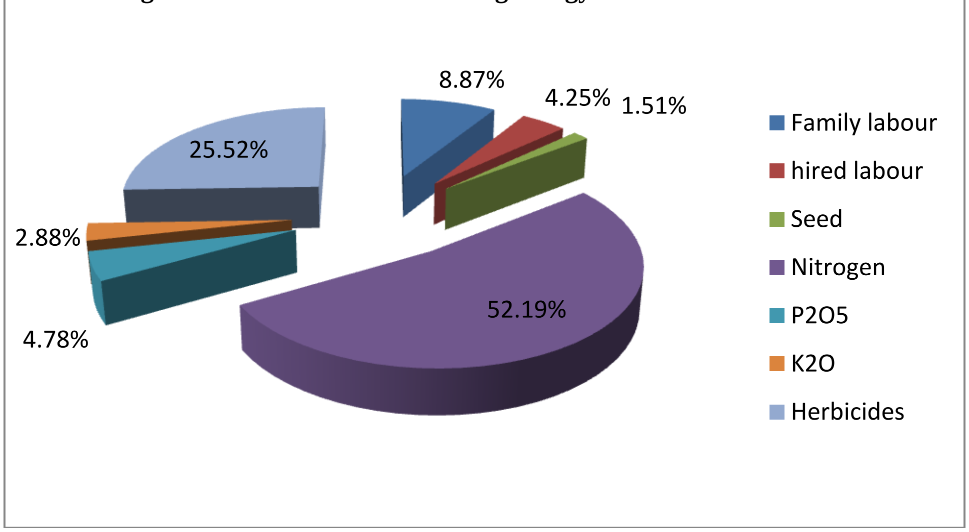
R^2 = 0.7996

Source: Computed from EMS computer print-out

However, the ESTR for hired labour, nitrogen, P_2O_5 and K_2O fertilizers were found to be 31.03%, 30.48%, 30.48% and 30.49%, respectively; indicating that these inputs were fairly efficiently used by the farmers in the studied area. High efficiency observed for hired labour is because little of this kind of labour is employed due to abundance of free family labour and in some cases sort temporary if need arise; while the efficiency observed for inorganic fertilizer is associated to the hike in its price which is due to cost push inflation, subsidy removal and arbitral currency devaluation which affect cost of importation of stereotype fertilizer which are mostly used in the study area. Sadiq *et al*., (2015) reported similar results in their studies on energy optimization in maize production in Niger State of Nigeria, while contrary results were reported in literature by Singh *et al.*, (2004) for wheat production in Punjab of India and Ranji *et al.*, (2013) for rice production in Mazandaran Province of Iran, respectively.

Furthermore, the ESTR percentage for total energy input was 34.14%, indicating that by adopting the recommendations obtained from this study, on average; approximately 34.14% equivalent to 1009.35 MJha^{-1} from total input energy in sorghum production could be saved without affecting productivity level. Singh *et al.*, (2004) reported that 15.9% (11305 MJha^{-1}) from total energy input for wheat production could be saved without affecting the yield level. In another study, the total energy saving reported by Chauhan *et al.*, (2006) was 1094 MJ ha^{-1} for rice production in West Bengal, India. In the same vein, Ranji *et al*., (2013) found that approximately 7.47% (4.57 GJha^{-1}) of overall energy resource used in rice production in Mazandaran Province of Iran could be reduced if all of the farmers operate efficiently. Also, Sadiq *et al.*, (2015) reported that about 32.62% equivalent to 768.89MJha^{-1} of total energy input consumed in maize production in Niger State of Nigeria could be saved if the farmers adopted the recommendations resulted from their study. Using this information, it is possible to advise the inefficient farmers regarding the better operating practices followed by his peers in order to reduce the input energy levels to the optimum values indicated in the analysis while maintaining the present output level achieved. Distribution of saving energy from different sources for sorghum production is shown in Figure 2. It is evident that Nitrogen fertilizer (52.19%) accounted for the maximum contribution to the total saving energy. However, summarized information showed agrochemical (biological) energy input contributed 85.37% to the total saving energy while industrial energy accounted for 14.63%. This is consistent with the result of studies conducted by Sadiq *et al.*, (2015) who reported that biological energy input had the highest potential for improving energy productivity in maize production. This justifies the previous studies by Sadiq (2015) who reported that non-renewable energy (nitrogen fertilizer and biocides) was the highest energy input consumed in cereal production in Niger State of Nigeria, and excessive usage of these chemical energy inputs in agriculture may create serious environmental consequences such as high nitrogen deposit in the environment and receiving H_2O, poor H_2O quality, carbon emission and contamination of the food chain. From the foregoing results it is strongly suggested that improving the usage pattern of these inputs be considered as priorities in providing significant improvement in energy productivity for sorghum production in the studied area. Improving energy use efficiency of human labour at farm level properly and creating enabling industrial environment to absorb excess labour would minimize wastages by inefficient farmers. Also, adopting better management technique, employing conservation tillage mulching technique and controlling input usage by performance monitoring can help to reduce the fertilizer and biocide energy inputs, thus, minimize their environmental impacts. Integrating legume into the crop rotation, application of composts, chopped residues, cultural and biological techniques for weed management and other soil amendments may increases soil fertility in the medium term, thereby reduce the need for chemical fertilizer energy inputs.

Figure 2: % Distribution of saving energy from different sources



Improvement of Energy Indices

The energy indices for sorghum production in actual and optimum energy use are presented in Table 8. It is obvious that by optimization of energy use, both the energy ratio and energy productivity indicators can improve by 51.85% and 50% respectively. Also, in optimum consumption of energy resources, the net energy indicator improvement by 11.20% would increase to 10021.55MJha^{-1}. However, the percentages of difference for specific, industrial, biological, direct, indirect, renewable non-renewable, commercial and non-commercial energies were -34.16%, -36.51%, -33.78%, -36.59%, -33.81%, -36.51%, -33.67% and -42.60% respectively, meaning that by optimization, these energy inputs would be reduced.

Moreover, by optimization process the total energy input consumed in sorghum production would reduce by 34.15% which translate into 1946.07MJha^{-1}. In summary, sorghum is a crop with relatively high requirements for non-renewable energy resources; its fertilizer energy requirement is high and it needs a high amount of biocide energy input. And these can be due to the facts that most farmers in the studied area don't have adequate knowledge on efficient input use and there is a common belief that increase use of energy resources will increase their productivity.

Table 8: Improvement of Energy Indices for Sorghum Production

Items	Unit	Qty in Actual Use (A)	Qty in Optimum Use (B)	Difference (%) {(B-A/A)}*100
Energy ratio	-	4.05	6.15	51.85
Energy productivity	KgMJ^{-1}	0.28	0.42	50
Specific energy	MJKg^{-1}	3.63	2.39	-34.16
Net energy	MJha^{-1}	9012.2	10021.55	11.20
Industrial energy	MJha^{-1}	404.50	256.83	-36.51
Biological energy	MJha^{-1}	2550.92	1689.24	-33.78
Direct energy	MJha^{-1}	361.95	229.50	-36.59
Indirect energy	MJha^{-1}	2593.47	1716.57	-33.81
Renewable energy	MJha^{-1}	404.50	256.83	-36.51
Non-renewable energy	MJha^{-1}	2550.92	1689.24	-33.78
Commercial energy	MJha^{-1}	2731.80	1811.98	-33.67
Non-commercial energy	MJha^{-1}	233.62	134.09	-42.60
Agro-chemical	%	21.32	86.80	307.13
Total input energy	MJha^{-1}	2955.42	1946.07	-34.15

Source: Computed from EMS computer print-out

Comparing Input Use Pattern of Efficient and Inefficient Farmers

The quantity of source wise physical inputs and output for efficient and inefficient farmers are shown in Table 9. The results showed that all energy inputs used by efficient farmers were less than that of inefficient ones. In summary the total energy input consumed in sorghum production by efficient units was lower than that of inefficient units. However, the energy inputs with highest difference were seeds and family labour; seeds and family labour energy inputs used by inefficient farmers were 27.85% and 27.84% higher than that of efficient units.

Excess of these energy inputs usages was because they are free and coupled with inadequate technical know-how resulting in wastage. Therefore, inefficient farmers should channel these excess into alternative uses, for example, excess family labour should be invested in alternative income generating ventures. Furthermore, total energy output and productivity of the inefficient farmers were found to be lower than that of efficient farmers.

Comparing Energy Indices of Efficient and Inefficient Farmers

The energy indices of efficient and inefficient units for sorghum production are presented in Table 10. Energy use efficiency of inefficient units was lower than that of efficient units, with approximate difference of 39.47%. Also, energy productivity, net energy, agrochemical energy ratio, of inefficient units was less than that of efficient units by approximately 38.46%, 20.95% and 283.02% respectively. However, the percentage difference for specific, industrial, biological, direct, indirect, renewable, non-renewable, commercial, non-commercial and total input energy were found to be higher than that of efficient units. Therefore, optimization of energy consumption using DEA would reduce energy wastages by inefficient units.

Table 9: Comparing Input Use Pattern of Efficient and Inefficient Sorghum Farmers

Item	Inefficient Farms (A)	Efficient Farms (B)	Difference (%) [(A-B)/A]*100
a. Inputs			
Family labour	236.80	170.88	27.84
Human labour	143.63	117.13	18.45
Seed	45.06	32.51	27.85
Nitrogen	1802.64	1430.88	20.63
P_2O_5	165.09	131.04	20.63
K_2O	99.65	79.10	20.62
Herbicides	593.13	471.59	20.49
Total input energy	3086	2433.08	21.16
b. Output			
Yield (kg)	798.36	877.20	-9.88
Total output energy	11735.84	12894.76	-9.88

Source: Computed from EMS computer print-out

Table 10: Comparing Energy Indices of Efficient and Inefficient Units

Items	Unit	Inefficient Farms (A)	Efficient Farms (B)	Difference (%) [(A-B)/A]*100
Energy ratio	-	3.80	5.30	-39.47
Energy productivity	$KgMJ^{-1}$	0.26	0.36	-38.46
Specific energy	$MJKg^{-1}$	3.87	2.77	28.42
Net energy	$MJha^{-1}$	8649.84	10461.68	-20.95
Industrial energy	$MJha^{-1}$	425.49	320.52	24.67
Biological energy	$MJha^{-1}$	2660.51	2112.56	20.60
Direct energy	$MJha^{-1}$	380.43	288.01	24.29
Indirect energy	$MJha^{-1}$	2705.57	2145.07	20.72
Renewable energy	$MJha^{-1}$	425.49	320.52	24.67
Non-renewable energy	$MJha^{-1}$	2660.51	2112.56	20.60
Commercial energy	$MJha^{-1}$	28489.20	2262.2	20.60
Non-commercial energy	$MJha^{-1}$	236.80	170.88	27.84
Agro-chemical	%	22.76	86.83	-283.02
Total input energy	$MJha^{-1}$	3086	2433.08	21.16
Total output energy	$MJha^{-1}$	11735.84	12894.76	-9.88
Productivity	$Kgha^{-1}$	798.36	877.20	-9.88

Source: Computed from EMS computer print-out

GHG Emissions of Efficient and Inefficient Units

The quantity of GHG emissions of efficient and inefficient farmers are shown in Table 11. The results indicated the GHG emissions of efficient and inefficient producers were 47.29 $KgCO_{2eq}$ h^{-1} and 59.12 $KgCO_{2eq}ha^{-1}$, respectively. It is evident that the total GHG emission of efficient units was less than of inefficient farmers by about 20.01% (11.83 $KgCO_{2eq}ha^{-1}$). However, the GHG emission differences for all the inputs except K2O were almost the same. Therefore, substitution of inorganic fertilizer with organic fertilizer, soil amendments, and application of cultural and biological controls to reduction of spraying operations is a major solution to agrochemical reduction.

Table 11: Comparison of GHG Emission for Inefficient and Efficient Units

Input	Inefficient ($KgCO_2ha^{-1}$) (A)	Efficient ($KgCO_2ha^{-1}$) (B)	Diff. ($KgCO_2ha^{-1}$)	Difference (%) [(A-B)/A]*100
Nitrogen	38.68	30.69	7.99	20.66
P_2O_5	2.97	2.36	0.61	20.54
K_2O	1.78	1.77	0.01	0.56
Herbicides	15.69	12.47	3.22	20.52
Total GHG emission	59.12	47.29	11.83	20.01

Source: Computed from EMS computer print-out

The amount of each input for efficient and inefficient units from GHG emissions point of view is shown in Figure 3. The graphical illustration show GHG emissions of nitrogen fertilizer to be highest followed by herbicides then P_2O and K_2O fertilizers for both cases. It can be inferred that nitrogen consumption of inefficient units was higher than that of efficient units. However, the main inputs of GHG creator were identical for efficient and inefficient units. Therefore, consumption of nitrogen fertilizer and herbicides should be reduced in all units. Also, P_2O_5 and K_2O consumption of inefficient units should be decreased according to the above-mentioned suggestions.

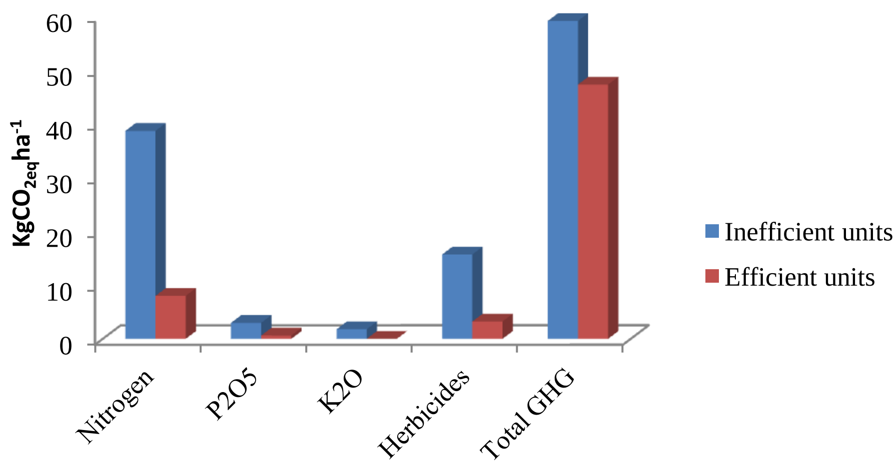


Figure 3: Comparison of GHG emission for efficient and inefficient units

Conclusion and Recommendations

The methodologies presented in this research demonstrate how energy use efficiency in sorghum production may improve by applying appropriate operational management tools to assess the performance of farmers. These methodologies helped to identify the impact of energy use from different inputs on output, measure efficiency scores of farmers, segregate efficient farmers from inefficient farmers and find the wasteful uses of energy by inefficient farmers. Results of DEA application indicated that there were substantial production inefficiencies among the farmers; so that, potential of approximately 21.16% reduction in total energy input use may be achieved if all farmers operated efficiently and assuming no other constraints on this adjustment. On an average, considerable savings in energy inputs may be obtained by adopting the best practices of high-performing ones in sorghum production process. Moreover, sorghum production in the studied area showed high sensitivity to non-renewable energy sources which may result in environmental deterioration and rapid rate of depletion of these energetic resources. The average yield of sorghum output for efficient and inefficient farmers were 877.20 $Kgha^{-1}$

and 798.36 $Kgha^{-1}$, respectively, indicating 9.88% yield decline in sorghum output of inefficient units. Furthermore, comparative results of GHG emissions for efficient units and inefficient units revealed the amount of CO_2 emissions in efficient units was less than that of inefficient units by 20.01% equivalent value of 11.83 $KgCO_{2eq}ha^{-1}$.

Adoption of more energy-efficient cultivation systems would help in energy conservation and better resource allocation. Some strategies such as providing better extension and training programs for farmers and use of advanced technologies should be developed in order to increase the energy efficiency of sorghum production in the studied area. The farmers should be trained with regard to the optimal use of inputs, especially, fertilizers and herbicides as well as employing the new production technologies i.e. development of renewable energy usage technologies, applying better management techniques, employing the conservation tillage and mulching techniques, use of nitrification inhibitors like neem-coated urea, utilization of alternative sources of energy such as organic fertilizers are suggested to reduce the environmental footprints of energy inputs and to obtain sustainable food production systems. Therefore, policies should emphasize on development of new technologies to substitute agrochemical with renewable energy sources aimed at efficient energy use and lowering environmental footprints. Also, policy on ban of stereotype agrochemical should be enacted thereby protecting the abiotic and biotic environment. Agricultural institutions in the studied area have an important role in establishing efficient energy and environmentally healthy sorghum production in the state i.e. research and extension activities should aim at reducing or cut down the emission of greenhouse gases. This may be achieved by altering some existing practices, adopting new technologies and learning from the experiences of other countries. For this purpose, people are to be educated and motivated, supplemented with regulatory measures taken by appropriate authorities.

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