Pathways to Reduce the Environmental Footprints of Energy Inputs in Sesame Production in Jigawa State, Nigeria

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***Abstract*—*This research investigates the pathways tto reduce the environmental footprints of energy inputs in sesame production in Jigawa State of Nigeria using data elicited from 99 sesame farmers via multi-stage sampling technique. Energy efficiency was studied and degrees of technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) were determined using data envelopment analysis (DEA). Additionally, wasteful uses of energy by inefficient farms were assessed and energy saving of different sources was computed. Results revealed that only 9.4% DMUs were technically efficient with average TE score of 0.624; based on BCC model 34.4% DMUs were identified to be efficient with mean PTE score of 0.79; while based on scale efficiency only 12.5% DMUs were efficient with mean SE score of 0.804. Furthermore it was observed that approximately 38.17% (1505.58MJha^{-1}) of overall input energies can be saved if performance of inefficient DMUs rose to a high level.*

***Keywords*—Energy, Efficiency, DEA, Sesame, Nigeria.**

I. INTRODUCTION

There exist a close relationship between agriculture and energy given that agricultural sector is both user and supplier of energy in the form of bio-energy. Nowadays, there has been intensification in energy usage in agricultural activities as a response to continued growth of human population, tendency for an overall improved standard of living and limited supply of arable land, consequently causing problems threatening public health and the environment. However, increased energy use in order to obtain maximum yields may not bring maximum profits due to increasing production costs, but rather deplete natural resources rapidly and considerably increasing the amount of contaminants in the environment. Therefore, any criteria used to assess sustainability of land use and management system must address the issues of the time. At the dawn of the 21st century, principal global issues include the accelerated greenhouse effect, emission of CO_2 and other GHGs from agricultural practices and food security in relation to soil and environmental degradation.

Efficient use of energy resources in agriculture is one of the principal requirements for sustainable agricultural productions; it provides financial savings, fossil resources preservation and air pollution reduction. For enhancing energy efficiency attempt must be made to increase the production yield or to conserve the energy input without affecting the output. Therefore, energy saving has been a crucial issue for sustainable development in agricultural systems. Development of efficient agricultural systems with low input energy compared to the output of food can reduces the greenhouse gas emissions from agricultural production systems.

II. METHODOLOGY

The economy of Jigawa State is largely characterized by informal sector activities with agriculture as the major economic activity. Most parts of the state lie within the Sudan Savannah with elements of Guinea Savannah in the southern part; enjoys vast fertile arable land to which almost all tropical crops could adapt. Multi stage sampling technique was used to generating a total sampling size of 99 respondents. In the first stage 3 LGAs *viz.* Taura, Malam-

Madori and Maigatari were purposively selected due to high intensity of sesame cultivation. The second stage involved random selection of 3 villages from each selected LGA; and the last stage involved selection of 11 respondents from each village using simple random sampling technique, given a total sample size of 99. However, only 96 valid questionnaires were retrieved. Instrument for data collection was pre-tested questionnaire coupled with interview schedule, which was administered on the respondents. Tool for data analysis was Data Envelopment Analysis (DEA)

Table 1: Equivalents for various sources of energy

Items	Unit	Equivalent MJ	Remarks
Human Labour	Man-hour	1.96	
Improved seeds	Kg	25.5	Processed
Nitrogen	Kg	60.60	
P_2O_5	Kg	11.1	
K_2O	Kg	6.7	
Herbicides	Litre	238	
Manure	Kg	0.3	
sesame product	Kg	25	

Empirical model

Data Envelopment Analysis

The DEA is 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. DEA is a linear programming model that attempts to maximize a service unit's efficiency within the performance of a group of similar service units that are delivering the same service. In their original paper Charnes *et al.*(1978) introduced the generic term "decision making units" (DMU) to describe the collection of firms, departments, or divisions which have multiple incommensurate inputs and outputs and which are being assessed for efficiency. Since then it has been successfully used in many different sectors to assess and compare the efficiency of DMUs. CCR model which was built on the assumption of constant returns to scale (CRS), was suggested by Charnes and Cooper (1984); also called global efficiency model. Later, Banker *et al.*(1984) introduced the BCC model based on variable returns to scale (VRS); also called the local efficiency model. DEA models are broadly divided into two categories on the basis of orientation: input-oriented and output-oriented. Input-oriented models have the objective of minimizing inputs while maintaining the same level of outputs, whereas output-oriented models 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. Efficiency models are given below:

The CCR Efficiency Model

It is also called technical efficiency model and the main assumption behind it is "constant returns to scale", under which the production possibility set is formed without any scale effect. As Charnes *et al.* (1978) reported the LP model deployed to generate the CCR efficiency factors of the DMUs considered is as follows.

The CCR model (to be solved for each DMU_{K0}):

$Max \quad \theta_{CCR} \quad (k_0) \quad = \quad \sum_{j=0}^{n} UjYjk0$ .... (1)

Subject to: $\sum_{j=0}^{n} UjYjk0$

$\sum_{i=0}^{m} \theta_I \quad X_i \quad k_0 \quad = \quad 1$ ……………………………………………………………… …………… (2)

$-\sum_{i=0}^{m} \theta_I X_i\, k_0 \;+\; \sum_{j=1}^{n} Uj\, Yjk \;\leq 0 \qquad U_j \geq 0, \quad \theta_j \geq 0$ ………………………………….. (3)

$k = 1, \ldots\ldots, k \qquad j = 1, \ldots\ldots, n \qquad i = 1, \ldots\ldots, m$

Where Uj is the weight for output j; θi is the weight for input i; m the number of inputs; n the number of outputs; K the number of DMU_S ; Yjk the amount of output j of DMU_K ; and xik the amount of input I of DMU_K

The BCC Efficiency Model

It is also called the pure technical efficiency model. The main assumption behind it is "variable returns to scale", under which the production possibility set is the convex combinations of the observed units. Banker *et al.* (1984) reported the LP model deployed to generate BCC efficiency factors of the DMUs is as follows. The BCC model (to be solved for each DMU_{K0}):

$Max \quad \theta_{BCC} \quad (k_0) \quad = \quad \sum_{j=0}^{n} UjYjk_0 \quad - \quad U \quad (k_0)$ ……………………………………………………. (4)

Subject to:

$\sum_{i=0}^{m} \theta_I \quad X_i \quad k_0 \quad = \quad 1$ ……………………………………………………………… ……………… (5)

$-\sum_{i=0}^{m} \theta_I X_i\, k_0 \;+\; \sum_{j=1}^{n} Uj\, Yjk \;- U\,(k_0) \leq 0 \qquad U_j \geq 0, \quad \theta_j \geq 0$ …………………………… (6)

$k = 1, \ldots\ldots, k \qquad j = 1, \ldots\ldots, n \qquad i = 1, \ldots\ldots, m$

The inefficiency that a DMU might exhibit may have different causes: whether it is caused by the inefficient operation of the DMU itself or by the disadvantageous conditions, under which the DMU is operating, is an important issue to be clarified. In this regard, comparisons of the CCR and BCC efficiency scores deserve attention. The CCR model assumes a radial expansion and reduction of all observed DMUs (and their nonnegative combinations are possible); while the BCC model only accepts the convex combinations of the DMUs as the production possibility set. If a DMU is fully (100%) efficient in both the CRR and BCC scores, it is operating at the most productive scale size. If a DMU has full BCC score, but a low CCR score, then it is locally efficient but not globally efficient due to its scale size. Thus, it is reasonable to characterize the scale efficiency of a DMU by the ratio of the two scores. So, scale efficiency is defined as:

$$\textbf{\textit{SE}} = \theta_{CCR}/\theta_{BCC} \quad \ldots\ldots (7)$$

Where, θ_{CCR} and θ_{BCC} are the CCR and BCC scores of a DMU, respectively. SE = 1 shows scale efficiency (or CRS) and SE < 1 indicates scale inefficiency. Scale inefficiency can be due to the existence of either increasing returns to scale (IRS) or decreasing returns to scale (DRS). Shortcoming of the SE score is that it does not demonstrate if a DMU is operating under IRS or DRS. This is resolvable by simply imposing non-increasing returns to scale (NIRS) condition in the DEA model. IRS and DRS can be determined by comparing the efficiency scores obtained by the BCC and NIRS models; so, if the two efficiency scores are equal, then DRS apply; else IRS prevail.

Energy saving target ratio (ESTR) helps to determine the inefficiency level of energy usage; index used is as follows:

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

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

III. RESULTS AND DISCUSSION

Efficiency scores of farmers

Distributional results of DMUs based on the efficiency scores obtained by the application of CCR and BCC DEA models are shown in Figure (1). It is evident that, about 9.4 percent (9 DMUs) and 33 percent (34.4 DMUs) from total farmers were recognized as efficient farmers under constant and variable returns to scale assumptions, respectively. However, 48 percent and 60 percent, with respect to technical and pure technical efficiency scores recorded efficiency scores between 0.6 and 1.00 scales. Also, when the BCC model was assumed, only approximately 2.1 percent had an efficiency score of less than 0.40; whereas, when the CCR model was assumed, approximately 13 percent DMUs had an efficiency score of less than 0.40. Furthermore, observed returns to scale estimation indicate that almost all technically efficient farmers (based on the CCR model) were operating at CRS, revealing optimum scale of their practices.

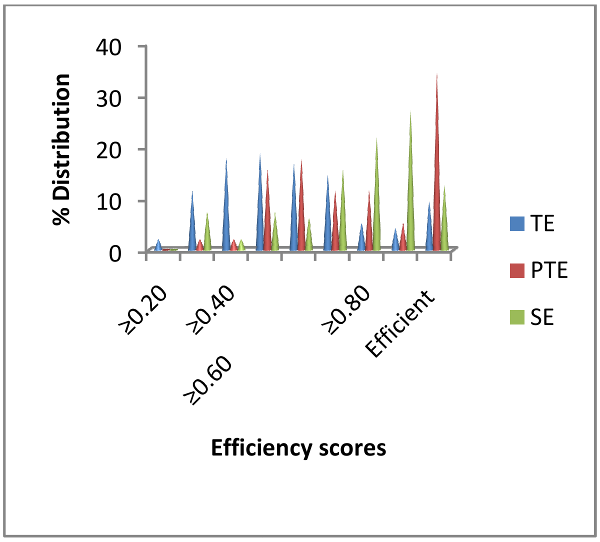

Fig.1: % Distribution of efficiency score

The summarized statistics for the three estimated measures of efficiency indicated the mean values of technical and pure technical efficiency scores to be 0.83 and 0.93, with technical and pure technical efficiency scores varying from 0.268-1.00 and 0.36-1.00 scales, respectively (Table 2).The wide variation in the technical efficiency implies that all the farmers were not fully aware of the right production techniques or did not apply them properly, while wide variation in pure technical efficiency indicates that the farmers were irrational in resource allocation at their disposal. For technical efficiency, farmers who had efficiency score of less than one, are inefficient in energy use, while for pure technical efficiency, target DMUs with less than one efficiency score are using more energy than required, thus, indicating ample scope for target farmers to improve their operational practices in enhancing their energy use efficiency for adjustment strategy. If technical efficiency is assumed, average farmers need to increase their technical efficiency by 37.6 percent; worst inefficient farmers need technical efficiency adjustment of 73.2 percent, and best inefficient farmers needs adjustment of 3.2 percent respectively to be on the frontier surface; while if adjustment for pure technical efficiency is assumed, average farmers need to reduce their energy inputs by 21 percent; worst inefficient farmers' needs 63.8 percent input reduction, and best inefficient farmers require 3.2 percent input reduction respectively, to be on the frontier surface. The average scale efficiency score was relatively low (0.804), indicating the disadvantageous conditions of scale size. This implies that if all the inefficient farmers operated at the most productive scale size, about 19.6 percent savings in energy use from different sources would be possible without affecting the yield level. Therefore, raising the yield and decreasing energy inputs consumption, the inefficient farmers can increase their energy efficiency.

Based on literature, technical, pure technical and scale efficiencies scores respectively, of 0.68, 0.78 and 0.88 for green house gas emission in maize farming in Niger State, Nigeria (Sadiq *et al.*, 2015); 0.85, 0.99 and 0.86 for greenhouse gas emission in nectarine production in Sari province of Iran (Qasemi-Kordkheili and Nabavi-Pelesaraei, 2014); 0.83, 0.98 and 0.84 for greenhouse gas emission in potato production in Esfahan province of Iran (Khoshnevisan *et al.*, 2013); 0.894, 0.965 and 0.922 for greenhouse gas emission in orange production in Guilan province of Iran (Nabevi-Pelesaraei *et al.*, 2014), and 0.972, 0.879 and 0.900 for greenhouse gas emission in cucumber farming in Iran (Omid *et al*., 2011) had been reported.

Table 2: Deciles frequency distributions of efficiency scores

Efficiency level	TE	PTE	SE
≥ 0.20	2(2.1)	0	0
≥ 0.30	11(11.5)	2(2.1)	7(7.3)
≥ 0.40	17(17.7)	2(2.1)	2(2.1)
≥ 0.50	18(18.8)	15(15.6)	7(7.3)
≥ 0.60	16(16.7)	17(17.7)	6(6.2)
≥ 0.70	14(14.6)	11(11.5)	15(15.6)
≥ 0.80	5(5.2)	11(11.5)	21(21.9)
≥ 0.90	4(4.2)	5(5.2)	26(27.1)
1.00	9(9.4)	33(34.4)	12(12.5)
Total	**96**	**96**	**96**
Minimum	**0.268**	**0.362**	**0.339**
Maximum	**1.00**	**1.00**	**1.00**
Mode	**1.00**	**1.00**	**1.00**
Mean	**0.624**	**0.79**	**0.804**
SD	**0.20**	**0.190**	**0.192**

Source: Computed from DEAP 2.1 computer print-out
( ): percentage

Return to scale properties

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 calculated values were compared. The same value for TE and NIRS indicates that the DMU has DRS, while different values imply that the farm has IRS. Results revealed RTS for some selected DMUs (Appendix), and indicates that DMUs *viz.* 1, 14-43, 46-47, 57-59, 65-80 that are efficient under the CRS model are both pure and scale efficient, and for inefficient farms, technological change is required for considerable changes in yield, while the RTS for all efficient farms based on technical efficiency were operating at CRS. However, it was observed that 12 DMUs, 74 DMUs and 10 DMUs had CRS, IRS and DRS respectively (Table 3). Therefore, a proportionate increase in all inputs leads to more 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 indicating the potential redistribution of resources between the farmers, and thus, enables them to achieve higher yield value

Table 3: Characteristics of farms with respect to return to scale

Scale	No. of farms	Mean energy output
Sub-optimal	74	11414
Optimal	12	19319.44
Super-optimal	10	18800

Source: Computed from DEAP 2.1 computer print-out

Ranking Analysis

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, because efficient farmers obviously follow good operational practices. However, among the efficient farmers, some show better operational practices than others, therefore, discrimination need to be made among the efficient farmers while seeking the best operational practices. In order to have the efficient farmers ranked, the number of times an efficient DMU appears in a referent set was counted, and the results obtained from the analysis showed that DMUs 1-2, 6-14, 24-30, 32-37, 39-43, 46-47, 57-58, 59-63, 65-67, 80-87 and 91appeared 10-3, 7-15, 9-1, 33-3, 4-3, 56-20, 21-1, 10-10, 15-3, 39-7 and 1 times in the referent set, respectively (Table 4); with farm 46 having the highest appearance in the referent set. These efficient farms can be selected by inefficient DMUs as best practice DMUs, making them a composite DMU instead of using a single DMU as a benchmark. 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 in the ranking. The results of such 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 4: Benchmarking of efficient DMUS

DMU(farm)	Frequency in referent set	Ranking	DMU(farm)	Frequency in referent set	Ranking
DMU46	56	1	**DMU06**	7	9
DMU80	39	2	**DMU83**	7	9
DMU32	33	3	**DMU39**	4	10
DMU57	21	4	**DMU02**	3	11
DMU47	20	5	**DMU37**	3	11
DMU14	15	6	**DMU43**	3	11
DMU65	15	6	**DMU67**	3	11
DMU01	10	7	**DMU30**	1	12
DMU59	10	7	**DMU58**	1	12
DMU63	10	7	**DMU91**	1	12
DMU24	9	8			

Source: Computed from DEAP 2.1 computer print-out

Performance Assessment

The performance assessment was investigated by comparing a particular DMU system with key competitors DMUs having best performance within the same group or another group performing similar functions, process called benchmarking. 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; summation of all intensity vectors in a benchmark DMU must be equal to 1. The results in Table 5 showed the worst inefficient DMUs (DMU89, DMU76 and DMU75) and the best inefficient DMUs (DMU31, DMU35, DMU38, DMU61 and DMU69). For instance, in the case of DMU89 and DMU76, the composite DMU that represents the best practice or reference composite benchmark DMU's is formed by the combination of DMU24 and DMU32.

This implies that DMU 89 and DMU76 are closer to the efficient frontier segment formed by these efficient DMUs, represented in the composite DMU. Selection of these efficient DMUs was made on the basis of their comparable level of inputs and output yield to DMU89 and DMU76. However, benchmark DMUs for DMU89 and DMU76 are expressed as 24(0.229) 32(0.771) for DMU89 and 24(0.241) 32(0.759) for DMU76, respectively, where 24 and 32 are the DMU numbers, while the values between brackets are the intensity vector λ for the respective DMUs. The high value of intensity vector λ for DMU32 (0.653) indicates that its level of inputs and output is closer to DMU75 compared to other DMUs.

Table 5: Performance assessment of farms

DMU	PTE score (%)	Benchmarks
DMU89	33.9	24(0.229) 30(0.771)
DMU76	33.9	24(0.241) 32(0.759)
DMU75	34.0	32(0.653) 42(0.347)
DMU31	99.8	80(0.263) 59(0.030) 47(0.134) 46(0.573)
DMU35	99.8	80(0.284) 47(0.111) 59(0.017) 46(0.588)
DMU38	99.9	47(0.010) 80(0.340) 46(0.380) 59(0.270)

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DMU61	99.9	47(0.229) 65(0.294) 14(0.230) 57(0.246)
DMU69	99.9	47(0.010) 80(0.340) 46(0.340) 59(0.270)

Source: Computed from DEAP 2.1 computer print-out

Comparing input use pattern of efficient and inefficient farmers

The quantity of source wise physical inputs and output for 12 most efficient and inefficient farmers based on CCR model were compared (Table 6). Results revealed that the use of all inputs by efficient farmers were less than that of inefficient farmers. However, use of herbicides caused the main difference between efficient farmers and inefficient ones; efficient farmers used approximately 41.33 percent less herbicides than inefficient farmers. Furthermore, production yield for inefficient framers was observed to be lower than that of efficient farmers, i.e approximately 57.15 percent less than the production yield obtained by efficient farmers.

Table 6: Amounts of physical inputs and output for efficient farmers and inefficient farmers

Input	Inefficient ($MJha^{-1}$) (A)	Efficient ($MJha^{-1}$) (B)	Difference (%) [(A-B)/A*100]
Human labour	675.84	609.10	9.88
Seed	88.28	83.18	5.78
Nitrogen	1307.97	989.09	24.38
P_2O_5	239.56	181.17	24.38
K_2O	144.48	109.36	24.31
SSP	681.64	470.97	30.91
Manure	480.32	390.98	18.60
Herbicides	321.23	188.45	41.33
Output (sesame kg)	12293.65	19319.44	-57.15

Source: Computed from DEAP 2.1 computer print-out

Setting realistic input levels for inefficient farmers

A pure technical efficiency score of less than one for a farmer implies at present conditions he is consuming higher energy values than required. Therefore, it becomes imperative to suggest realistic levels of energy to be used from each source for every inefficient farmer in order to avert wastage of energy. Table 7 provides information for setting realistic input levels *viz.* average energy usage in actual and optimum conditions (MJ ha^{-1}), possible energy savings and ESTR percentage for different energy sources. It is evident that, total energy input could be reduced to 1505.58 $MJha^{-1}$ while maintaining the current production level and also assuming no other constraints factors. Optimum energy required for agro-chemicals *viz.* NPK fertilizer, SSP fertilizer and herbicides are 566.7$MJha^{-1}$, 296.9$MJha^{-1}$ and166.96 MJ ha^{-1}, respectively.

Moreover, optimum energy required for manure, human labour and seeds energy inputs were 196.65$MJha^{-1}$, 251.2$MJha^{-1}$ and 27.17$MJha^{-1}$, respectively.

Furthermore, ESTR results revealed that if all farmers operated efficiently, reductions in Nitrogen, P_2O_5, K_2O, SSP fertilizer, herbicides, human labour, manure and seed energy inputs by 33.6%, 34.50%, 33.65%, 44.21%, 52.75%, 40.36%, 35.82% and 30.27% would be possible without affecting the yield level. These energy inputs were not efficiently utilized due to excess use. High percentages of agro-chemical energy inputs can also be interpreted to be attributed to subsidized prices and free availability of these inputs in the study area. Accurate agro-chemical management by increasing its profitability with respect to crops, and losses reduction by improving management practices can improve energy use. Moreover, findings revealed ESTR percentage for total energy input to be 38.17 percent, implying that, by adopting the recommendations reported in this study, on the average about 38.17 percent (1505.58$MJha^{-1}$) from total input energy in sesame production could be saved without affecting the yield level. Other findings such as Sadiq *et al.*(2015) reported that 36.2 percent (768.89$MJha^{-1}$) from total energy input in small-scale maize production in Niger State, Nigeria could be saved without affecting the yield level; Sattari-Yuzbashkandi *et al.* (2014) found that 26.53 percent (21809.96 $MJha^{-1}$) from total energy input in open-field grape production in East-Azerbaijan of Iran could be saved without affecting the yield level; Qasemi-Kordkheili and Nebavi-Pelesaraei (2014) reported that 3.25 percent (1309$MJha^{-1}$) from total energy input in nectarine orchard production in Sari region of Iran could be saved without affecting the yield level; Nebavi-Pelesaraei *et al.* (2014) discovered that 12.9 percent (3314$MJha^{-1}$) from total energy input in orange production in Guilan province of Iran could be saved without affecting the yield level; Khoshnevisan *et al.* (2013) found that 13 percent (1506.63 $MJha^{-1}$) from total energy input among potato growers in province of Esfahan in Iran could be saved without affecting productivity level; Mousavi-Avval *et al.*(2012) reported that 16.4 percent (1571.6$MJha^{-1}$) from total energy input in sunflower production in Golestan province of Iran could be saved without affecting the yield level. Also,

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Mousavi-Avval *et al.* (2011) reported about 20 percent of overall resources in soybean production could be reduced if all the farmers operated efficiently. Therefore, it is possible to advise the inefficient farmers regarding better operating practices followed by his peers in order to reduce the input energy levels to the optimum levels indicated in the analysis while maintaining the present output level achieved.

Table.7: Energy saving (MJha-1) from different sources if recommendations of study are followed

Input	Actual energy used ($MJha^{-1}$)	Optimum energy requirement ($MJha^{-1}$)	Energy saving	ESTR (%)
Human labour	701.27	450.07	251.2(16.69)	35.82
Seed	89.76	62.59	27.17(1.81)	30.27
Nitrogen	1296.84	860.32	436.52(28.99)	33.66
P_2O_5	237.54	155.59	81.95(5.44)	34.50
K_2O	143.31	95.08	48.23(3.20)	33.65
SSP	671.55	374.65	296.9(19.72)	44.21
Manure	487.2	290.55	196.65(13.06)	40.36
Herbicides	316.54	149.58	166.96(11.09)	52.75
Total energy input	3944.01	2438.43	1505.58	38.17

Source: Computation from DEAP 2.1 computer print-out( ): percentage

Figure 2 reveals distribution of saving energy from different sources in sesame production. It was evident that maximum contribution to the total saving energy was 28.99 percent from Nitrogen fertilizer. However, agrochemical *viz.* NPK fertilizer, SSP fertilizer and herbicides energy inputs contributed 68.44 percent to the total saving energy. From these findings, the researchers/authors opined that improving usage pattern of these inputs should be considered as priorities for providing significant improvement in energy productivity for sesame production in the study area. Applying a better management technique, employing the conservation tillage methods and also controlling input usage by performance monitoring can help to reduce fertilizer energy inputs, thus minimizing their environmental impacts. Moreover, integrating legume's into the crop rotation, application of composts, chopped residues or other soil amendments may increases soil fertility in the medium term, thus reduce the need for chemical fertilizer energy inputs.

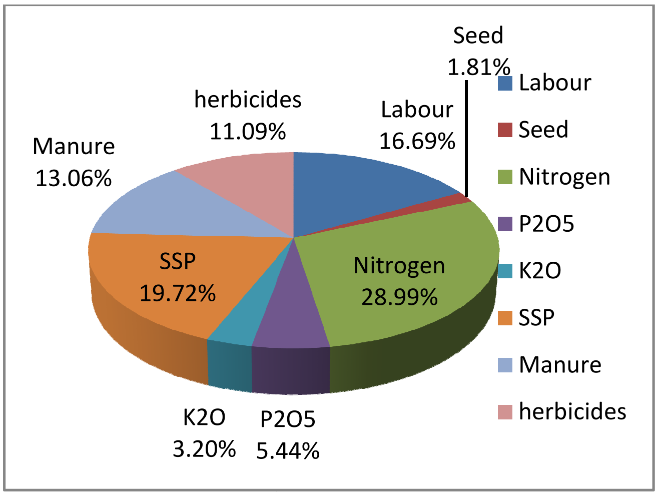

Fig.2: Total saving energy (1505.58 MJ/ha)

Improvement in energy indices

The energy indices for sesame production in optimum use of energy are given in Table 8. Evidently, by optimization of energy use both the energy ratio and energy productivity indicators respectively, can improve by 61.68 percent and 61.54 percent. In optimum consumption of energy inputs, improvement in net energy indicator by approximately 16.32 percent will increase to 10733.57$MJha^{-1}$.Therefore, it can be inferred that sesame is a crop with relatively high requirements for nonrenewable energy resources; its fertilizer requirement was high and consumes relatively high amount of herbicides. It's evident that most farmers in the study area lack adequate knowledge on efficient input use and there is a common belief that productivity increase with increase use of energy resources. Findings from this research demonstrate how energy use efficiency in sesame production may be improved by application of operational management tools to assess farmers' performance. Averagely, considerable savings in energy inputs may be obtained by adopting best practices of better-performing farmers in crop production process. Adoption of energy-efficient cultivation systems will help in energy conservation and better resource allocation. Strategies such as providing better extension and training programs for farmers, and use of advanced technologies should be developed in order to increase energy efficiency of agricultural crop productions in the study area. Moreover, farmers should be trained with respect to optimal use of inputs, especially fertilizers and herbicides application, as well as employing the new production technologies. Also, based on these findings agricultural institutes in the study area are advised to establish energy-efficient and environmentally healthy sesame production systems in the study area.

Table 8: Comparison between energy indices and improved energy indices for sesame Production

Items	Unit	Qty in Actual use	Qty in optimum use	Difference (%)
Energy ratio	-	3.34	5.40	61.68
Energy productivity	KgMJ^{-1}	0.13	0.21	61.54
Specific energy	MJKg^{-1}	7.49	4.63	38.18
Net energy	MJha^{-1}	9227.99	10733.57	16.32
Direct energy	MJha^{-1}	701.27	450.07	35.82
Indirect energy	MJha^{-1}	3242.74	1988.36	38.68
Renewable energy	MJha^{-1}	791.03	512.66	35.19
Non-renewable energy	MJha^{-1}	3152.98	1925.77	38.92
Total input energy	**MJha^{-1}**	**3944.01**	**2438.43**	**38.17**

IV. CONCLUSION AND RECOMMENDATIONS

The study empirically investigates optimization of energy used in sesame production in Jigawa State, Nigeria using Data Envelopment Approach. This approach 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 identify wasteful uses of energy by inefficient farmers. Results indicated that there was substantial production inefficiencies among the farmers; in such a way, that 21% potential reduction in total energy input use may be achieved if all farmers operate efficiently and assuming no other constraints on this adjustment. Comparison between actual and optimum energy used revealed that 1505.58MJha^{-1} can be saved if all inefficient DMUs use energy based on this research recommendations. Since, findings revealed that sesame production in the study area showed a high sensitivity to non-renewable energy sources which may result in both environmental deterioration and rapid rate of depletion of these energetic resources, policies emphasizing on development of new technologies to substitute agro-chemical with renewable energy sources keeping in view efficient use of energy and lowering environmental footprints should be enacted. Furthermore, development of renewable energy usage technologies such as better management techniques, employing conservation tillage methods, utilization of alternative sources of energy such as organic fertilizers are suggested to reduce the environmental footprints of energy inputs and ensure sustainable food production systems.

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APPENDIX: Technical and Scale Efficiencies and Returns to Scale

DMU	TE	PTE	NIRS	SE	RS	DMU	TE	PTE	NIRS	SE	RS
1	1.00	1.00	1.00	1.00	CRS	31	0.559	0.560	0.559	0.998	DRS
2	0.919	1.00	0.919	0.919	IRS	32	0.636	1.00	0.636	0.636	IRS
3	0.756	0.821	0.756	0.920	IRS	33	0.654	0.744	0.654	0.880	IRS
4	0.58	0.704	0.58	0.824	IRS	34	0.619	0.725	0.619	0.854	IRS
5	0.577	0.616	0.577	0.936	IRS	35	0.64	0.641	0.64	0.998	DRS
6	0.554	1.00	0.554	0.554	IRS	36	0.745	1.00	0.745	0.745	IRS
7	0.642	0.865	0.642	0.742	IRS	37	0.843	1.00	0.843	0.843	IRS
8	0.272	0.535	0.272	0.508	IRS	38	0.706	0.706	0.706	0.999	DRS
9	0.467	0.610	0.467	0.766	IRS	39	0.784	1.00	0.784	0.784	IRS
10	0.482	0.622	0.482	0.775	IRS	40	0.716	0.805	0.716	0.890	IRS
11	0.465	0.840	0.465	0.554	IRS	41	0.705	0.714	0.705	0.986	IRS
12	0.464	0.594	0.464	0.781	IRS	42	0.629	0.629	0.629	1.00	CRS
13	0.363	0.482	0.363	0.753	IRS	43	1.00	1.00	1.00	1.00	CRS
14	1.00	1.00	1.00	1.00	CRS	44	0.674	1.00	0.674	0.674	IRS
15	0.754	0.819	0.754	0.921	IRS	45	0.828	0.863	0.828	0.960	IRS
16	0.64	0.823	0.64	0.778	IRS	46	1.00	1.00	1.00	1.00	CRS
17	0.533	0.643	0.533	0.829	IRS	47	1.00	1.00	1.00	1.00	CRS
18	0.504	0.776	0.504	0.650	IRS	48	0.607	1.00	0.607	0.607	IRS
19	0.554	0.626	0.554	0.884	IRS	49	0.481	0.975	0.481	0.493	IRS
20	0.577	0.583	0.577	0.989	IRS	50	0.442	1.00	0.442	0.442	IRS
21	0.679	1.00	0.679	0.679	IRS	51	0.834	0.875	0.834	0.953	IRS
22	0.672	0.900	0.672	0.747	IRS	52	0.632	0.632	0.632	1.00	CRS
23	0.707	0.710	0.707	0.995	DRS	53	0.667	0.733	0.667	0.909	IRS
24	0.812	1.00	0.812	0.812	IRS	54	0.679	0.689	0.679	0.987	DRS
25	0.476	0.537	0.476	0.886	IRS	55	0.778	0.937	0.778	0.830	IRS
26	0.441	0.509	0.441	0.865	IRS	56	0.952	0.956	0.952	0.996	DRS
27	0.583	0.587	0.583	0.994	DRS	57	1.00	1.00	1.00	1.00	CRS
28	0.536	0.591	0.536	0.908	IRS	58	0.863	1.00	0.863	0.863	IRS
29	0.762	0.825	0.762	0.924	DRS	59	1.00	1.00	1.00	1.00	CRS
30	0.686	1.00	0.686	0.686	IRS	60	0.743	0.805	0.743	0.923	IRS
DMU	**TE**	**PTE**	**NIRS**	**SE**	**RS**	**DMU**	**TE**	**PTE**	**NIRS**	**SE**	**RS**
61	0.922	0.923	0.922	0.999	DRS	91	0.390	1.00	0.390	0.390	IRS
62	0.538	1.00	0.538	0.538	IRS	92	0.346	1.00	0.346	0.346	IRS
63	0.500	1.00	0.500	0.500	IRS	93	0.423	0.506	0.423	0.838	IRS
64	0.769	1.00	0.769	0.796	IRS	94	0.515	0.667	0.515	0.772	IRS
65	1.00	1.00	1.00	1.00	CRS	95	0.268	0.673	0.268	0.398	IRS
66	0.690	0.785	0.690	0.878	IRS	96	0.463	0.637	0.463	0.726	IRS
67	0.968	1.00	0.968	0.968	IRS						
68	0.734	0.787	0.734	0.933	IRS						
69	0.706	0.706	0.706	0.999	DRS						
70	0.539	1.00	0.539	0.539	IRS						
71	0.513	0.615	0.513	0.835	IRS						
72	0.423	0.500	0.423	0.845	IRS						
73	0.562	0.675	0.562	0.833	IRS						
74	0.336	0.362	0.336	0.930	IRS						

75	0.340	1.00	0.340	0.340	IRS						
76	0.339	1.00	0.339	0.339	IRS						
77	0.474	0.474	0.474	1.00	CRS						
78	0.349	0.381	0.349	0.918	IRS						
79	0.572	0.685	0.572	0.835	IRS						
80	1.00	1.00	1.00	1.00	CRS						
81	0.499	0.528	0.499	0.947	IRS						
82	0.411	0.807	0.411	0.509	IRS						
83	0.357	1.00	0.357	0.357	IRS						
84	0.456	0.648	0.456	0.703	IRS						
85	0.555	0.693	0.555	0.801	IRS						
86	0.396	0.506	0.396	0.784	IRS						
87	0.375	0.525	0.375	0.714	IRS						
88	0.475	0.552	0.475	0.861	IRS						
89	0.339	1.00	0.339	0.339	IRS						
90	0.497	0.592	0.497	0.840	IRS						