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Global Warming and Tragedy of the Commons: Comparative Evidence of Greenhouse Gas Emission (CO_2) between Efficient and Inefficient Sesame Producers in Jigawa State of Nigeria

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Abstract: *Data for this research were elicited from 99 sesame farmers in Jigawa State, Nigeria 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. Furthermore, the effect of energy optimization on greenhouse gas (GHG) emission was investigated and the total amount of GHG emission of efficient farms was compared with inefficient ones. Results revealed that only 9.4% DMUs were technically efficient and the average TE score was 0.624; based on BCC model 34.4% DMUs were identified to be efficient and the mean PTE score was 0.79; while based on scale efficiency only 12.5% DMUs were efficient, and the mean SE score was 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. Comparative results of GHG emissions for efficient farmers and inefficient farmers revealed that the amount of CO_2 emissions in efficient DMUs was less than inefficient DMUs. Moreover, findings inferred that, by energy optimization, total GHG emission can be reduced to an estimated value of 21.87 KgCO_2eqha^{-1}.Generally, the application of data envelopment analysis method can improve energy efficiency and GHG emissions in sesame production, significantly.*

Keywords: *DEA; Efficiency; GHG emission; Sesame; Nigeria.*

1. INTRODUCTION

One of the five global problems is the threat of a long-run increase in the surface temperature of the earth. Global warming must be considered on an entirely different scale from that of most other environmental issues. The effects of global warming, or "greenhouse effect" as it is popularly called, are long-term and largely irreversible. The potential effects of climate change are dramatic; no single country contributes more than small fraction of greenhouse gases. Data for 1985 suggested that developed countries' contribution to CO_2 emission was 3.95 billion tonnes and this was expected to rise to 6.71 billion tonnes by 2025.

Developing countries, on the other hand, account for only 1.29 billion tonnes of CO_2 emission in 1985, and the projected increase for 2025 was 5.47 billion tonnes of carbon. Thus, globally in 1985, 5.24 billion tonnes of CO_2 was emitted which was projected to increase to 12.18 billion tonnes by 2025.

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The CO_2 emissions are projected to increase by 2.6 percent annually, with USA been the largest contributor globally, accounting for nearly 18 percent. Climate change is expected to damage agriculture in some areas but aid it in others. The principal damage will arise from heat stress, decreased soil moisture, and an increased incidence of pests and diseases. In addition, warmer temperatures could cause the growing cycle of many plants to accelerate, allowing less time for plant development before maturity. Increased rainfall intensity could increase soil erosion in some areas, whereas other areas could be affected by drought. Unchecked climate changes over the long-term will lead to mass migration, political changes, economic chaos and agricultural disruptions. The tragedy of the commons suggests that since the atmosphere is freely accessible, countries will have no incentive to control the emission of greenhouse gasses from the territory. On the contrary, they should calculate that any controls applied unilaterally will penalize industry and the country's competitive position, while providing only a marginal benefit that will be enjoyed by all countries. Thus the tragedy of the commons suggests that the precautionary principle is unlikely to be applied, because countries act in defence of their own self-interest.

On top of this, the differential impact of global warming with some countries enjoying, better climatic conditions or having the resources to defend themselves against the impact of flooding and drought etc. will encourage the urgency of the global situation. The consequences of global warming clearly indicate two things:

1. both developed and developing nations have good reason to worry about global warming;
2. global cooperation is an important consideration when addressing global warming issues.

In line with this, the responses to the global warming issue can be analysed as technical response and policy response. Technical response attempts at reducing emission of greenhouse gases and at increasing the CO_2 absorbing capacity of the earth. However, there are several studies (Sadiq *et al.*, 2015; Nabevi-Pelesaraei *et al.*, 2014; Qasemi-Kordkheili and Nabavi-Pelesaraei, 2014; Khoshnevisan *et al.*, 2013)- though not many and not from all areas- which showed beyond doubt that the nature and methods of agricultural developments are posing problems to the environment which can bring about harmful effects in an ample measure. Thus, before it is too late, policy measures should be adopted to restore the balance between agriculture and environment. The approach as it is rightly pointed out by researchers should be combination of economic, institutional and technological measures.

Hypotheses Testing

$H_0$1: Technical efficiency scores of farmers are unequal

H_A1: Technical efficiency scores of farmers are equal

$H_0$2: Pure technical efficiency scores of farmers are unequal

H_A2: Pure technical efficiency scores of farmers are equal

$H_0$3: Scale efficiency scores of farmers are unequal

H_A3: Scale efficiency scores of farmers are equal

2. 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_{K_0}):

$$\text{Max } \theta_{CCR}(k_0) = \sum_{j=0}^{n} UjYjk_0 \quad \text{...(1)}$$

Subject to: $\sum_{j=0}^{n} UjYjk_0$

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

$$-\sum_{i=0}^{m} \theta_I X_i k_0 + \sum_{j=1}^{m} UjYjk \le 0 \quad U_j \ge 0, \theta_j \ge 0 \quad \text{...(3)}$$

$k = 1, ..., k$ $j = 1, ..., n$ $i = 1, ..., m$

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}):

$$Max_{BCC}(k_0) = \sum_{i=0}^{n} UjYjk_0 - U(k_0) \quad \text{...(4)}$$

Subject to:

$$-\sum_{i=0}^{m} \theta_1 X_i k_0 = 1 \quad \text{...(5)}$$

$$-\sum_{i=0}^{m} \theta_1 X_i k_0 + \sum_{j=0}^{n} UjYjk - U(k_0) \le 0 \quad U_j \ge 0, \theta_j \ge 0 \quad \text{...(6)}$$

$k = 1, ..., k$ $j = 1, ..., n$ $i = 1, ..., m$

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:

$$SE = \theta_{CCR}/\theta_{BCC} \qquad ...(7)$$

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:

$$ESTR\,(\%) = \frac{\text{Energy saving target}}{\text{Actual energy input}} \times 100 \qquad ...(8)$$

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.

GHG Emissions

CO_2 emission coefficients of agricultural inputs were used to quantifying GHG emissions in sesame cultivation. GHG emission was calculated by multiplying the input application rate by its corresponding emission coefficient (Table 2).

Table 2
GHG emission coefficients of agricultural inputs

Items	Unit	GHG coefficient (kg CO_2eq. unit^{-1})
Nitrogen	Kg	1.3
P_2O_5	Kg	0.2
K_2O	Kg	0.2
Herbicides	L	6.3
Field cultivation	ha^{-1}	4.0
Fertilizer spreading	ha^{-1}	7.6
Spraying herbicides	ha^{-1}	1.4
Harvesting	ha^{-1}	10.0

RESULTS AND DISCUSSION

Efficiency Scores of Farmers

The results of distribution of DMUs based on the efficiency score obtained by the application of CCR and BCC DEA models is shown in Figure (1). As it is evident, 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. Moreover, 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.

The summarized statistics for the three estimated measures of efficiency are given in Table (3). The results revealed that the mean values of technical and pure technical efficiency scores were 0.83 and 0.93, respectively; with technical and pure technical efficiency scores varying from 0.268-1.00, and 0.36-1.00 scales for technical efficiency and pure

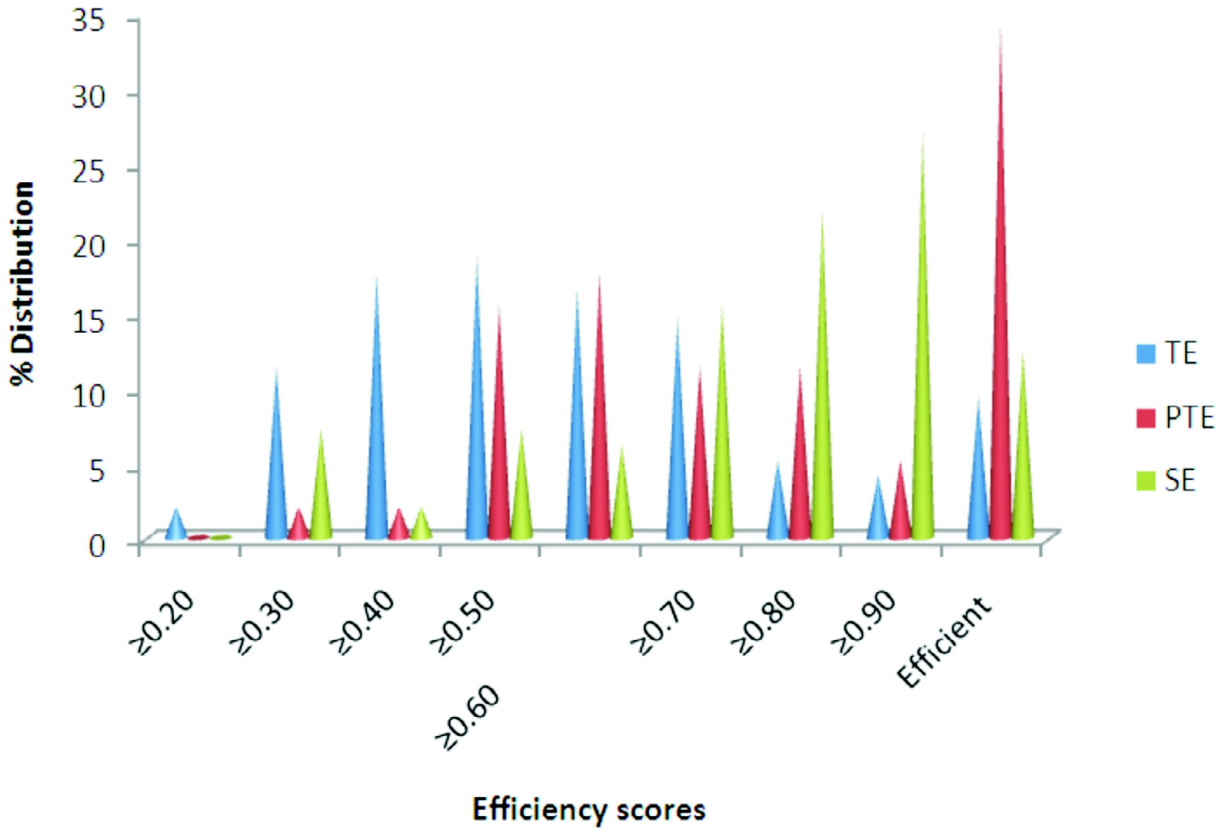

Figure 1: % Distribution of efficiency score

technical efficiency respectively. 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 3
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

Hypotheses Testing

The results of hypotheses testing using Gini coefficient in conjunction with Lorenz curve revealed that farmers had equal efficiencies scores as shown by Gini coefficient indexes for TE, PTE and SE respectively (Table 3a-3c). However, these efficiencies parameters were visualized by the Lorenz curve (Figure 1a-1c). Therefore, all the null hypotheses were rejected and the alternatives accepted.

Table 3a
Gini coefficient indexes for hypotheses testing

Items	*TE*	*PTE*	*SE*
Sample Gini coefficient	0.1797	0.1347	0.1283
Estimate of population value	0.1815	0.1361	0.1297

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 4). 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 4
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 the Efficient Farmers

In this study for ranking the 21 extreme efficient farmers, the cross efficiency scores in each cell of cross efficiency matrix were calculated based on the CCR model, and these efficient DMUs were compared together from efficiency point of view (Table 5). The results and standard deviation of superior efficient DMUs indicates DMU with Nos. 24, 58 and 91 with cross efficiency scores of 0.538, 0.574 and 0.680 respectively, had the highest average cross efficiency values; and can be used as criterion for inefficient farmers or as benchmarking terms for establishing best practice management. Therefore, it is the opinion of the researchers that inefficient DMUs should use the inputs closer to these reference DMUs.

Table 5
Average cross efficiency score for 21 superior efficient farmers

DMU	ACE	SD	Farmer	ACE	SD
DMU01	0.208	0.283	DMU47	0.197	0.239
DMU02	0.446	0.376	DMU57	0.208	0.237
DMU06	0.256	0.322	DMU58	0.574	0.603
DMU14	0.227	0.252	DMU59	0.242	0.295
DMU24	0.538	0.653	DMU63	0.338	0.293
DMU30	0.335	0.273	DMU65	0.232	0.228
DMU32	0.245	0.500	DMU67	0.236	0.221
DMU37	0.267	0.489	DMU80	0.337	0.217
DMU39	0.490	0.418	DMU83	0.277	0.338
DMU43	0.485	0.403	DMU91	0.680	0.519
DMU46	0.412	0.230			

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 (Table 6). 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 ë 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 6 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 ë 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 6
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)
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 7). 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.

Setting Tealistic 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

Table 7
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.

levels of energy to be used from each source for every inefficient farmer in order to avert wastage of energy. Table 8 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 $MJha^{-1}$ and 166.96 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

Table 8
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

(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, 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.

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.

Improvement in Energy Indices

The energy indices for sesame production in optimum use of energy are given in Table 9. 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

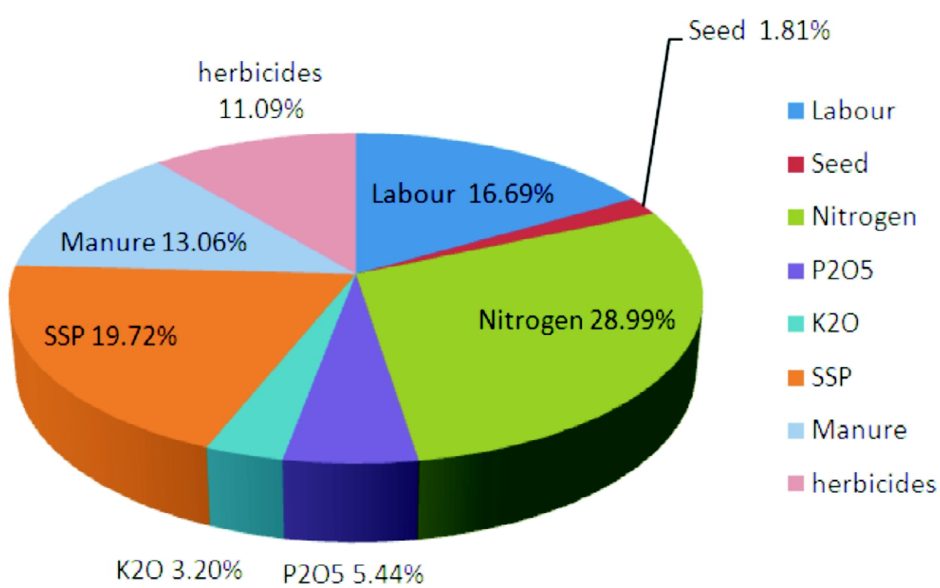

Figure 2: Total saving energy (1505.58 MJ/ha)

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 9
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

Source: Field survey, 2015.

Comparison of GHG Emissions between Efficient and Inefficient Farmers

GHG emission of efficient and inefficient DMUs was investigated to determine the role of energy optimization in environmental condition of sesame production in the study area (Table 10). Results revealed the GHG emissions of 12 most efficient and 84 inefficient farmers to be 40.57 kg CO_{2eq} and 56.87 kg CO_{2eq} ha^{-1}, respectively. As it can be seen, the total GHG emission of inefficient units was more than GHG emission of efficient farmers by approximately 28.57 percent. The highest difference between efficient and inefficient units was observed in Nitrogen fertilizer (42.08%). Therefore, nitrogen fertilizer consumption of inefficient units should be close to that of most efficient. For this purpose, the selection of recommended finding dose is the best solution. Also, applying cultural and biological controls are major solution to reduction of chemical fertilizers and biocide.

Table 10
Comparison of GHG emissions between efficient and inefficient farmers

Input	*Inefficient ($KgCO_2ha^{-1}$) (A)*	*Efficient ($KgCO_2ha^{-1}$) (B)*	*Difference [(A-B)/A]*100*
1. Human Labour			
Field cultivation	0.112	0.1	10.7
Fertilizer application	0.0228	0.0228	0
Herbicides application	0.0056	0.0042	25
Harvesting	0.0592	0.0518	12.5
2. Nitrogen	28.05	21.22	24.4
3. P_2O_5	4.216	3.26	25.1
4. K_2O	3.237	2.448	24.4
5. SSP	12.282	8.486	30.9
6. Herbicides	8.505	4.998	41.5
Total	56.5	40.57	28.2

Source: Computation from DEAP 2.1 computer print-out.

Figure 3 displays the amount of each input for efficient and inefficient units from GHG emissions point of view. The results indicated that the GHG emission of Nitrogen was highest; followed by SSP fertilizer and then biocide (herbicide). It can be observed, that Nitrogen fertilizer consumption of inefficient units was more than that of efficient units. However, most values of the main inputs of GHG creator for efficient and inefficient were relatively not closer. Therefore, Nitrogen fertilizer, SSP fertilizer and herbicides consumption should be reduced in all units.

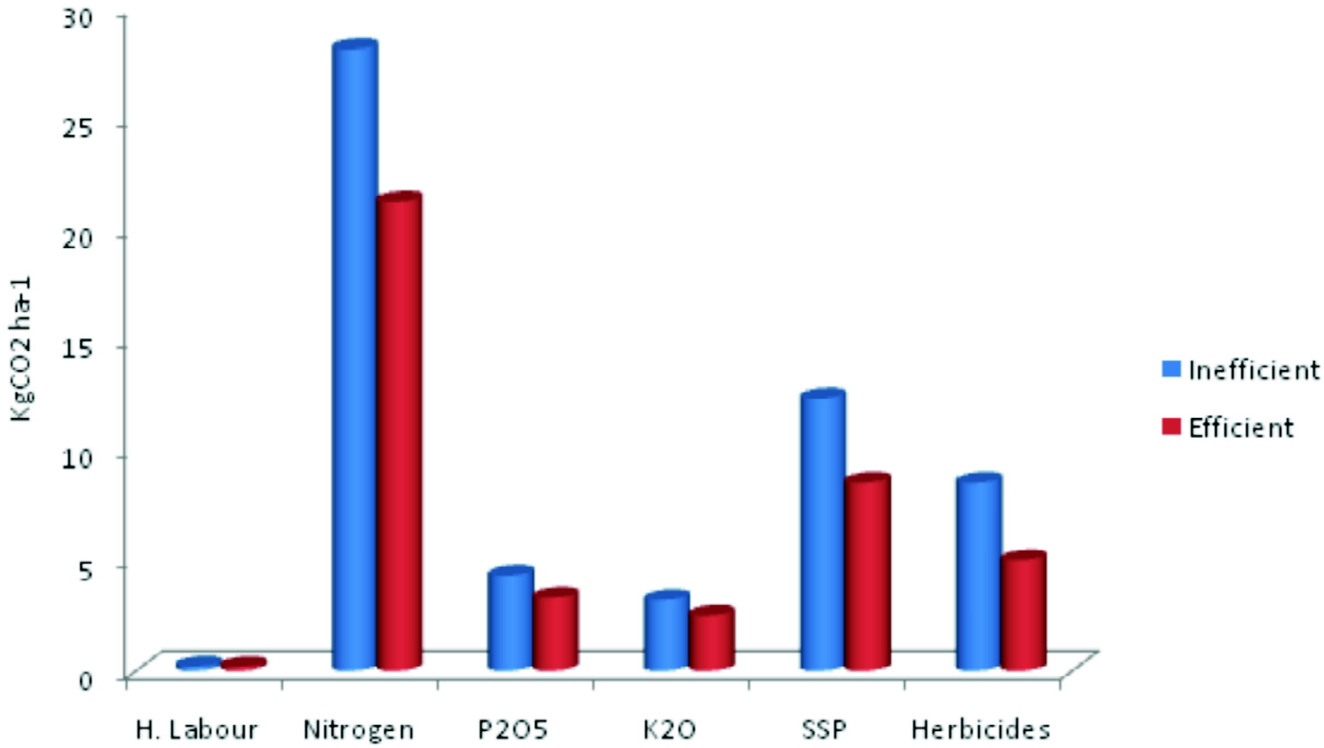

Figure 3: The quantity of GHG emission of Sesame production®

Reduction of GHG Emission for Sesame Farmers

GHG emission of efficient and inefficient DMUs was investigated to determine the role of energy optimization in environmental condition of sesame production in the study area (Table 11). The total GHG emissions of actual and optimum are 56 $kgCO_2eq\ ha^{-1}$ and 34 kg $CO_2eq.ha^{-1}$, respectively. From the results, it was observed that most amount of CO_2 emission was related to chemical fertilizers, and then followed by biocide (herbicides).

Therefore, energy consumption can be reduced by improving some agricultural practices and technological changes in inefficient DMUs, thereby reducing the GHG emission in the study area. Furthermore, results indicated that decreasing actual GHG emission by 39.29 percent will reduce GHG emission to 22 $kgCO_2eqha^{-1}$; total GHG emissions can be reduced by about 22 $kgCO_2eqha^{-1}$. So, it can be inferred that energy consumption had a direct relationship with GHG emissions.

Table 11
Amounts of GHG emission for actual and optimum

Input	Actual ($KgCO_2ha^{-1}$)	Optimum ($KgCO_2ha^{-1}$)	GHG reduction ($KgCO_2ha^{-1}$)
1. H. Labour			
Field cultivation	0.116	0.076	0.04
Fertilizer application	0.0228	0.015	0.0078
Herbicides application	0.0056	0.0042	0.0014
Harvesting	0.0592	0.037	0.0222
2. Nitrogen	27.82	18.46	9.4
3. P_2O_5	4.28	2.80	1.5
4. K_2O	3.21	2.13	1.1
5. SSP	12.1	6.75	5.4
6. Herbicides	8.38	4.02	4.4
Total GHG emission	56	34.02	21.87

Source: Computed from DEAP 2.1 computer print-out.

Figure 4 displays the share of each potential input in total GHG reduction in sesame production. The results indicated that Nitrogen fertilizer had the highest share in GHG emissions reduction (43%), followed by SSP fertilizer with 24.7% and biocide (herbicide) with 20.1%. Therefore, using renewable sources of energy can lead to cultivation with less GHG emission.

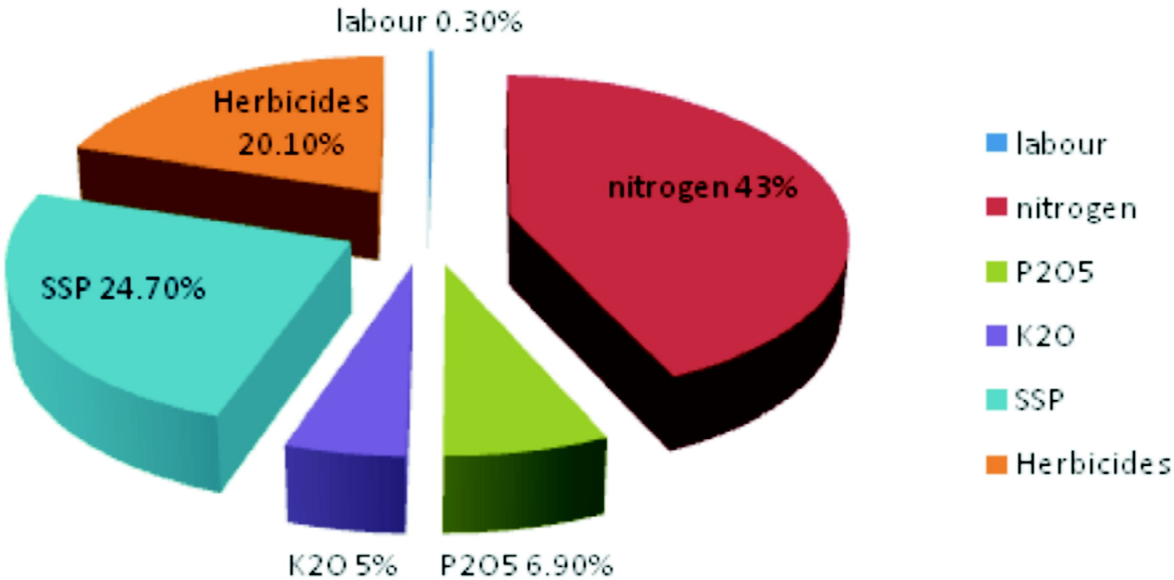

Figure 4: Share of each input in GHG emission reduction

CONCLUSION AND RECOMMENDATIONS

The study investigates energy efficiency in sesame production in Jigawa State, Nigeria using non-parametric (DEA) approach to determine farmers' efficiency. This methodology 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 operated efficiently and assuming no other constraints on this adjustment. Comparison between actual and optimum energy use revealed that 1505.58MJha^{-1} can be saved if all inefficient DMUs use energy based on the recommendations of this study.

The comparative results of GHG emissions for efficient farmers and inefficient farmers revealed that the amount of CO_2 emissions in efficient DMUs was less than inefficient DMUs. Based on results, it was observed that the total GHG emission in sesame production in the study area can be reduced to the value of 21.87KgCO_2 ha^{-1}. However, it was evident 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.

Therefore, 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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