



## Comparison of GHG emissions of inefficient and efficient small scale maize farmers in Niger state of Nigeria using data envelopment analysis

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### General Note

Article is recommended to print as color version in recycled paper. *Save Trees, Save Climate.*

## ABSTRACT

This research empirically compared GHG emissions between efficient and inefficient maize producers in Niger State, Nigeria using Data Envelopment Analysis (DEA). Data for the study were obtained from Kuta agricultural zone in the state viz. 120 active maize farmers using multi-stage sampling technique. Instruments for data were pre-tested questionnaire coupled with interview schedule. Energy efficiency of maize farmers was studied and degrees of overall technical efficiency (CCR), pure technical efficiency (BCC) and scale efficiency (SE) were determined using Data Envelopment Analysis (DEA). Additionally, wasteful uses of energy by inefficient DMUs (farms) were examined, and energy saving of different sources estimated. Furthermore, the effect of energy optimization on greenhouse gas (GHG) emission was investigated and the total amount of GHG emission of efficient DMUs was compared with inefficient DMUs. Results revealed that approximately 9.2% of the farmers were technically efficient with an estimated mean TE of 0.68. Furthermore, when BCC model was assumed, 24 farmers (DMUs) were identified to be locally efficient (20%), with mean PTE of 0.78. From the results, it was inferred that 32% (768.89MJ ha<sup>-1</sup>) of overall input energies can be saved if the performance of inefficient DMUs (farms) rose to a high level. Comparative results of GHG emissions for efficient farmers and inefficient farmers revealed that the amount of CO<sub>2</sub> emissions in efficient DMUs was less than inefficient DMUs. Generally, application of data envelopment analysis method can significantly improve energy efficiency and GHG emissions in maize production in the state.

**Keywords:** DEA; Energy; GHG Emission; Inefficient Vs Efficient; Maize; Nigeria

## 1. INTRODUCTION

Ecological disorders are operating harshly on the poor of whom so much concern is shown all over. The exploiters' are often the affluent people and the sufferer, the poor, who more than anything else depend on the prosperity of agriculture in the country-side. Although the village poor-agricultural labour, small and marginal farmers are partly themselves responsible for the environmental deterioration around them, yet the facts still remains that they have been getting life support from the natural resources without which they could not survive. This natural support has vanished as a result of unscientific exploitation of natural resources. In some cases, the damages are quite high and are adversely affecting even the successful implementation of poverty alleviation programmes. However, it can be discussed earlier how new agricultural technologies have resulted in environmental degradation (Akinnubi et al. 2016). It is argued, that traditional agriculture has also been acting against nature. It is true that some traditional practices such as reckless grazing, forest clearing, bush burning and other related things acted against environment, but these could be overcome through proper awareness and widespread education. The damage caused by the commercialization of traditional pursuits is irreparable and that has to be checked. Constant disorders in agro-ecological conditions will certainly threaten long-run perspectives of agricultural growth. This research brings out the importance of diversified farming and use of organic fertilizers in order to check ecological disorders. There are several studies (Sadiq *et al.* 2016; Sadiq *et al.*, 2015; Nabavi-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. Therefore this research is timely, given that it ought to create an innovative mechanism on how to tackle global warming/climate change as it relate to agriculture.

## 2. METHODOLOGY

Niger state is an agrarian state in Nigeria, and has been in the forefront in the production of food crops and subsequent feeding of the country at large. The study made use of multi stage sampling technique to collect primary data from a total sample size of 120 farmers. The first stage involved purpose selection of one agricultural zone out of the three zones in the state; namely Kuta zone due to its conspicuous importance in maize crop production; second stage involved random selection of three LGAs, namely, Minna, Bosso and Shiroro, respectively, based on preponderance of small-scale maize farmers; third stage involved random selection of four villages from each selected LGAs, and, the last stage involved simple random selection of ten active maize farmers from each selected villages, thus, gave a total sample size of 120. Instrument for data collection was pre-tested questionnaire coupled with interview schedule, which was administered on the respondents. Data were collected on fortnight basis, during the 2014 cropping season. Tools for data analysis were Energy index, Lorenz curve and Gini coefficient, and Data Envelopment Analysis (DEA).

**Table 1** Equivalents for various sources of energy

Items	Unit	Equivalent MJ	Remarks
Labour	Man-hour	1.96	
Improved seeds	Kg	15.2	Processed
Nitrogen	Kg	60.60	
P <sub>2</sub> O <sub>5</sub>	Kg	11.1	
K <sub>2</sub> O	Kg	6.7	
Herbicides	Litre	238	
Maize product	Kg (Dry mass)	14.7	The main output are grains

**Table 2** GHG emission coefficients of agricultural inputs

Items	Unit	GHG coefficient (kg CO <sub>2</sub> eq. unit <sup>-1</sup> )
Nitrogen	Kg	1.3
P <sub>2</sub> O <sub>5</sub>	Kg	0.2
K <sub>2</sub> O	Kg	0.2

### Empirical model

**1. Gini Coefficient:** It is a measure of statistical dispersion developed by the Italian statistician Corrado Gini and published in his paper "variability and Mutability" (Italian: *Variabilita e mutabilita*). The Gini index is defined as a ratio of the areas on the Lorenz curve. The formula is given as follows:

$$G = A/0.5 = 2A-1-2B \dots\dots\dots (1)$$

**2. Total Factor Productivity Index:** O'Donnell (2008) generalizes this idea to the multiple-output multiple input case by formally defining the total factor productivity (TFP) of a firm to be the ratio of an aggregate output to an aggregate input. The model is given below:

$$TFP_i = Q_i/X_i \dots\dots\dots (2)$$

Where,

$Q_i = Q$  ( $q_i$ ) is an aggregate output,

$X_i = X$  ( $x_i$ ) is an aggregate input, and;

$Q$  (.) and  $X$  (.) are non-negative, non-decreasing and linearly homogeneous aggregator functions

### 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). It is also called the global efficiency model. Later, Banker *et al.* (1984) introduced 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. 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  $DMU_{k0}$ ):

$$\text{Max } \theta_{CCR}(k_0) = \sum_{j=0}^n U_j Y_{jk0} \dots\dots\dots (3)$$

Subject to:  $\sum_{j=0}^n U_j Y_{jk0}$

$$\sum_{i=0}^m \theta_i X_i k_0 = 1 \dots\dots\dots (4)$$

$$-\sum_{i=0}^m \theta_i X_i k_0 + \sum_{j=1}^n U_j Y_{jk} \leq 0 \quad U_j \geq 0, \theta_j \geq 0 \dots\dots\dots (5)$$

$$k = 1, \dots, k \quad j = 1, \dots, n \quad i = 1, \dots, m$$

Where  $U_j$  is the weight for output  $j$ ;  $\theta_i$  is the weight for input  $i$ ;  $m$  the number of inputs;  $n$  the number of outputs;  $K$  the number of  $DMU_s$ ;  $Y_{jk}$  the amount of output  $j$  of  $DMU_k$ ; and  $x_{ik}$  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  $DMU_{k0}$ ):

$$\text{Max } \theta_{BCC}(k_0) = \sum_{j=0}^n U_j Y_{jk0} - U(k_0) \dots\dots\dots (6)$$

Subject to:

$$\sum_{i=0}^m \theta_i X_i k_0 = 1 \dots\dots\dots (7)$$

$$-\sum_{i=0}^m \theta_i X_i k_0 + \sum_{j=1}^n U_j Y_{jk} - U(k_0) \leq 0 \quad U_j \geq 0, \theta_j \geq 0 \dots\dots\dots (8)$$

$$k = 1, \dots, k \quad j = 1, \dots, n \quad i = 1, \dots, m$$

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:

$$\text{SE} = \theta_{CCR} / \theta_{BCC} \dots\dots\dots (9)$$

Where,  $\theta_{CCR}$  and  $\theta_{BCC}$  are the CCR and BCC scores of a DMU, respectively. By definition, SE cannot be greater than one. In analysis of efficient and inefficient DMUs, the energy saving target ratio (ESTR) index used is as follows:

$$ESTR (\%) = \frac{\text{Energy saving target} \times 100}{\text{Actual energy input}} \dots\dots\dots (10)$$

Where, energy saving target is the total amount of input that could be saved without decreasing output level. 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<sub>2</sub> emission coefficients of agricultural inputs were used to quantifying GHG emissions in maize cultivation. GHG emission was calculated by multiplying the input application rate by its corresponding emission coefficient (Table 2).

## **3. RESULTS AND DISCUSSION**

### **3.1 Measuring Efficiency of Farmers (DMUs)**

The summarized statistics for the three estimated measures of efficiency are presented in Table 3a, while individual-wise statistics for the three measures of efficiency are given in Table (3b). The results revealed a mean efficiency scores of 0.68, 0.78 and 0.88, respectively, for overall technical, pure technical and scale efficiency. The efficiency scores for overall technical efficiency ranged from 0.225 to 1.00; pure technical efficiency hovered between 0.34 to 1.00; and scale efficiency scores varied from 0.225 to 1.00. The wide variation in these efficiency scores implies that virtually all the farmers were not fully aware of the right production techniques or did not apply them properly. The CCR mean efficiency score of 0.68 implies that 32percent of the overall resources could be saved by raising the performance of these DMUs to the highest level, thus making them frontier farmers. However, some CCR-inefficient DMUs moved toward the BCC-efficient frontier. Furthermore, the worst inefficient DMUs records CCR efficiency score of 0.225 and implies that 77.5 percent of the overall resources could be saved by raising their performance to the frontier level. The BCC mean efficiency score of 0.78, implies that DMUs are wasting resources, and a reduction in the use of the energy resources by 22 percent will give them the same yield level obtained at the present BCC mean efficiency score, thus, by downsizing their inputs, they will be operating on the frontier. However, the worst affected DMU have a BCC efficiency score of 0.34, and required large quantum of resource energy downsizing to be efficient, and at the same time maintain the same yield level obtained at this worse efficiency score point.

The mean scale efficiency score was 0.88, relatively below the frontier, revealing disadvantageous conditions of scale size. This indicates that if all inefficient farmers operated at the most productive scale size, about 12 percent savings in energy use from different sources would be possible without affecting the yield level. However, It should be noted that if mean scale efficiency score is less than the BCC mean efficiency score, then, it can be inferred that scale inefficiency is the cause of overall inefficiency, but if greater than the BCC mean efficiency score, overall inefficiency is attributable to inefficient in management practices. Consequently, the low mean efficiency scores of 0.68 and 0.78 from CCR and BCC results, respectively in comparison to the mean scale efficiency score of 0.88, implies that inefficiency in maize production in the study area was due to managerial factors and not the scale of operation. Therefore, task lies on policy makers to devote time and resources in extension education and offering of farm advisory services. The current policy thrust in the state need to be reviewed if the efficiency which bothers on the entrepreneurial competence is to be enhanced.

Evidently, about 9.2 percent and 20 percent of the DMUs from total sample size were identified as fully efficient DMUs under CCR and BCC returns to scale assumptions, respectively, because their efficiency scores are 1.00, that is, lies on the frontier surface. Furthermore, findings revealed that approximately 8.3 percent, which in equivalent is ten (10) DMUs were discovered to be locally efficient, given that they are on the frontier surface with respect to BCC, and below the frontier surface with respect to CCR. In other words, it means these DMUs have full BCC scores, but a low CCR scores. Moreover, 9.2 percent of the DMUs were fully efficient with scale efficiency score of 1.00, that is, they operate on the frontier surface. This implies that these set of DMUs operate at the most productive scale size, and are termed globally efficient due to their scale sizes.

Also, when the CCR model is assumed, 40.8 percent are closer to the frontier, because they had an efficiency scores that is equal or greater than the CCR mean efficiency score of 0.68; whereas, when the BCC model is assumed, 31.7 percent are closer to the frontier, given that they recorded an efficiency scores which is equal or greater than the BCC mean efficiency score of 0.78. The results of distribution of the DMUs based on the efficiency scores obtained by CCR, BCC and scale efficiencies are shown in Figure 1. Hitherto, Figure (1b-1d) gave an in-depth pattern of distribution of these efficiencies between the DMUs using Lorenz curve in conjunction with Gini coefficient. The lorenze curve (Fig.1b) indicated more equal distribution of overall technical efficiency scores

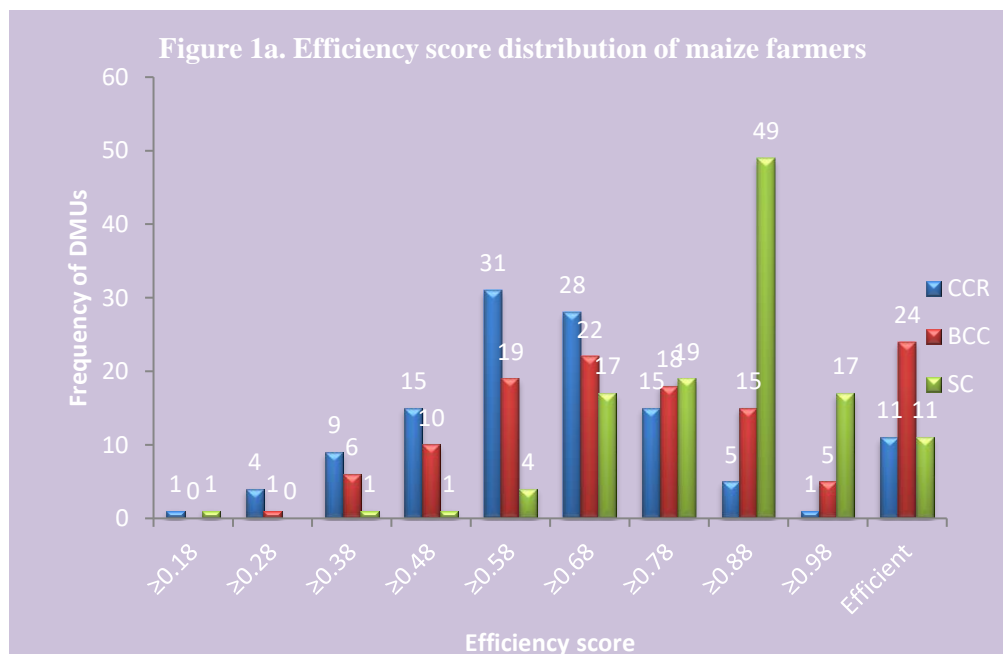
among the DMUs, as can be observed from the Lorenze curve which was not farther away from the line of equality; and this was justified by the sample Gini coefficient index which was 0.146. If the BCC was assumed (Fig.1c), the equality in distribution of efficiency scores was more than what was obtained under CCR, with sample Gini index of 0.129; however, farmers exhibit high equality in scale efficiency score distribution (0.0738) (Fig.1d), and by this it can be concluded that efficiency scores of these DMUs are relatively closer to each other.

**Table 3a** Deciles frequency distribution of efficiencies scores of maize farmers (DMUs)

Efficiency level	CCR (Overall technical efficiency)	BCC (Pure efficiency)	Scale efficiency
≥ 0.18	1 (0.8)	0 (0)	1 (0.8)
≥ 0.28	4 (3.3)	1 (0.8)	0 (0)
≥ 0.38	9 (7.5)	6 (5)	1 (0.8)
≥ 0.48	15 (12.5)	10 (8.3)	1 (0.8)
≥ 0.58	31 (25.8)	19 (15.8)	4 (3.3)
≥ 0.68	28 (23.3)	22 (18.3)	17 (14.2)
≥ 0.78	15 (12.5)	18 (15)	19 (15.8)
≥ 0.88	5 (4.2)	15 (12.5)	49 (40.8)
≥ 0.98	1 (0.8)	5 (4.2)	17 (14.2)
1.00	11 (9.2)	24 (20)	11 (9.2)
<b>Mean</b>	<b>0.68</b>	<b>0.78</b>	<b>0.88</b>
<b>Maximum</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>
<b>Minimum</b>	<b>0.225</b>	<b>0.344</b>	<b>0.225</b>
<b>Mode</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>
<b>SD</b>	<b>0.177</b>	<b>0.180</b>	<b>0.129</b>

Source: Computed from DEA Input approach (VRS) result.

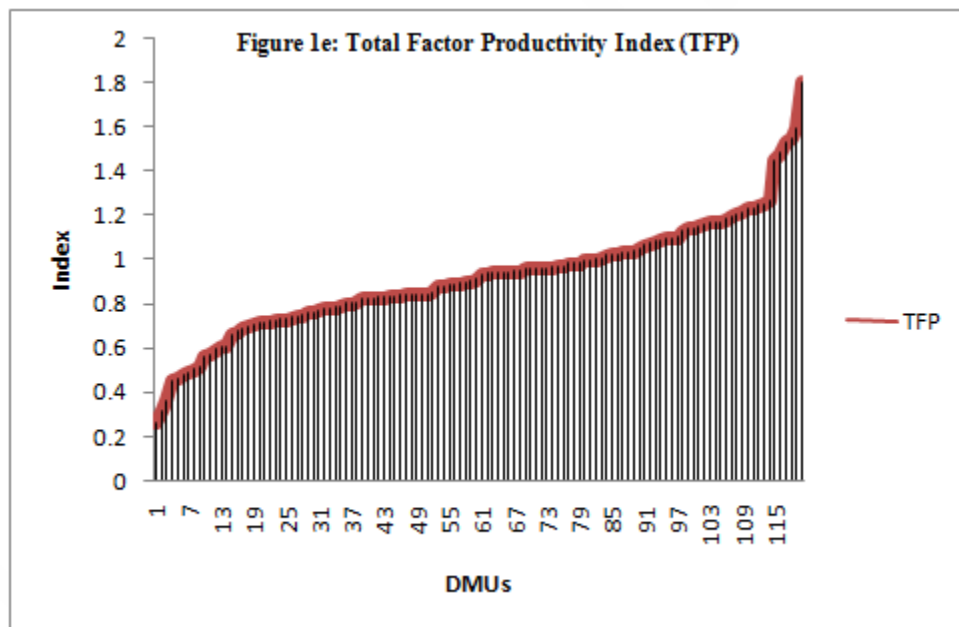
Note: ( ) relative percentage (%)



### 3.1.1 Return to scale properties

For the inefficient DMUs, the causes of inefficiency may be either inappropriate scale or misallocation of resources. Inappropriate scale suggests that the DMUs are not taking advantage of economies of scale, while misallocation of resources refers to inefficient energy input combinations. In this study, scale efficiencies were relatively high. Therefore, efficiencies were mainly due to improper

energy input usage. The results of returns to scale estimation indicated that all of the technically efficient farmers (based on the CCR model) were operating at CRS, showing the optimum scale of their practices, i.e, 14 percent were operating at CRS, 15 percent inefficient ones were operating at DRS and approximately 73.3 percent inefficient units were operating at IRS, which indicates that for considerable changes in yield, technological change is required (Table 3b). Also, result shows that there is small scale inefficiency in the study area. This implies that most of the DMUs should be smaller than their present size in order to achieve higher production given the available input mix. This was justified by TFP index mean score value of 0.92, which informs us that average productivity is 8 percent less than the maximum productivity that is possible using the technology available in 2014 maize production season in the study area. The minimal standard deviation index (0.258), implies that majority of the DMUs have their productivity hovering around the average TFP index. The TFP index for DMUs ranges between 0.27 to 1.81, with minimum and maximum TFP index of 0.27 and 1.81, respectively. It can be inferred that the DMUs with least TFP index value had productivity that is 73 percent less than the maximum productivity possible using available technology in the study period, while DMUs with maximum TFP, tells us that productivity of such DMUs is 81 percent above the maximum productivity that is possible using the same available technology during the study period in the study area. Furthermore, the mean scale efficiency score been below the frontier surface (0.88) informs us that the entire productivity shortfall is due to both technical and managerial inefficiencies. Therefore, more effort in extension services need to be geared by policy makers in other to sustain the viability of maize production in other not to jeopardize the current food security status of this crop in the state (Pabitra Aryal, 2015); (Table 3b). The distribution of the DMUs TFP index is depicted graphically in Figure 1e, and an in-depth pattern of distribution between these DMUs was examined using Lorenz curve in conjunction with Gini coefficient (Fig. 1f). Graphical visualization of the Lorenz curve showed an equal distribution of TFP index among the DMUs, which means they obtained a TFP index that is close to each other. This was justified by the value of the sample Gini coefficient index (0.153)



### 3.2. Comparative performance assessment to best key competitors (peer weight)

Performance assessment may 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. Efficient DMUs can be selected by inefficient DMUs as best practice of 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  $\lambda$  in the inputs and outputs of the respective efficient DMUs. BCC is modeled by setting the convexity constraint. The summation of all intensity vectors in a benchmark DMU must be equal to 1. Table (5) shows the worst inefficient DMUs (MF18 and MF25) and the best inefficient DMUs (MF28, MF68, MF70, MF73 and MF64). For instance, in the case of MF18 the composite DMU that represents the best practice or reference composite benchmark DMU is formed by the combination of MF09, MF77, MF02 and MF88. This means that MF18 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 yield to MF18. In Table (4a), the benchmark DMU for MF18 is expressed

as 9(0.248) 77(0.629) 2(0.004) 88(0.119), where 9, 77, 2 and 88 are the DMUs numbers while the values in the brackets are the intensity vector  $\lambda$  for the respective DMUs. The higher value of the intensity vector  $\lambda$  for MF77 (0.855) indicates that its level of inputs and output is closer to MF25 compared to the other DMUs.

**Table 4a** Comparative performance assessment to best key competitors (peer weight)

DMUs (Farmers)	BCC (PTE) score	Benchmarks
MF18	0.344	9(0.248) 77(0.629) 2(0.004) 88(0.119)
MF25	0.394	77(0.885) 98(0.145)
MF28	0.982	52(0.078) 84(0.217) 77(0.704)
MF68	0.982	84(0.217) 52(0.078) 77(0.704)
MF70	0.982	84(0.217) 52(0.075) 77(0.704)
MF73	0.982	52(0.078) 84(0.217) 77(0.704)
MF63	0.993	89(0.094) 113(0.747) 88(0.117) 77(0.043)

Source: Computed from DEA Input approach (VRS) result.

### 3.3. Comparative performance assessment to best key competitors (peer count)

Peer count summary is the number times each firm is a peer for another (Table 4b). Six DMUs became a peer 20 or more than 20 times for other DMUs. These DMUs were identified as robustly efficient DMUs since their production practices are such that they were frequently used to construct the efficient frontier for the other farms. In other words, these DMUs are very efficient since they appear more frequently as peers for other DMUs, thus, serve as the best practice DMUs to others in the study area. These efficient DMUs should be seen as role model and reference benchmarks for other DMUs with low or zero peer count if their objective is to become more scale efficient. The researcher referred to these six DMUs as spark plugs, because they are very efficient since they appear more frequently as peers for other DMUs, thus, serve as the best practice DMUs to others in the study area. Furthermore, the research suggest that the extension agents should liaise and make use of this spark plugs as reference pivot for adoption of improved technology on this crop and other closely related cereal crops in the study area if the need arises.

**Table 4b** Comparative performance assessment to best key competitors (peer count)

DMU (Farm)	Peer count	DMU (Farm)	Peer count
MF02	32	MF87	2
MF09	58	MF88	45
MF14	4	MF89	24
MF37	4	MF90	7
MF52	11	MF94	1
MF57	3	MF96	10
MF74	17	MF98	39
MF77	78	MF109	12
MF83	2	MF113	10
MF84	11		

Source: Computed from DEA Input approach (VRS) result.

### Comparing input use pattern of efficient and inefficient farmers

The quantity of source wise physical inputs and output for inefficient and five most efficient farmers based on BCC model were compared (Table 5). Results revealed that the use of all inputs by inefficient farmers were more than that of efficient farmers. However, use of herbicides and Nitrogen caused the main difference between inefficient and efficient ones; efficient farmers used approximately 21.16 percent and 19.19 percent less of herbicides and Nitrogen fertilizer respectively, than inefficient farmers. Furthermore, production yield for inefficient framers was observed to be lower than that of efficient farmers; approximately 3.76 percent less than the production yield obtained by efficient farmers facing the same technology.

**Table 5** Amounts of physical inputs and output for efficient farmers and inefficient farmers

Input	Inefficient (MJha <sup>-1</sup> ) (A)	Efficient (MJha <sup>-1</sup> ) (B)	Difference (%) [(A-B)/A*100]
Family labour	125.68	67.72	46
Hired labour	86.12	76.64	11
Seed	27.31	23.5	13.95
Nitrogen	711.48	574.93	19.19
P <sub>2</sub> O <sub>5</sub>	130.31	123.63	5.13
K <sub>2</sub> O	78.66	74.62	5.14
Herbicides	359.93	283.78	21.16
Output (maize kg)	10948.65	11360.63	-3.76

Source: Computed from DEAP 2.1 computer print-out

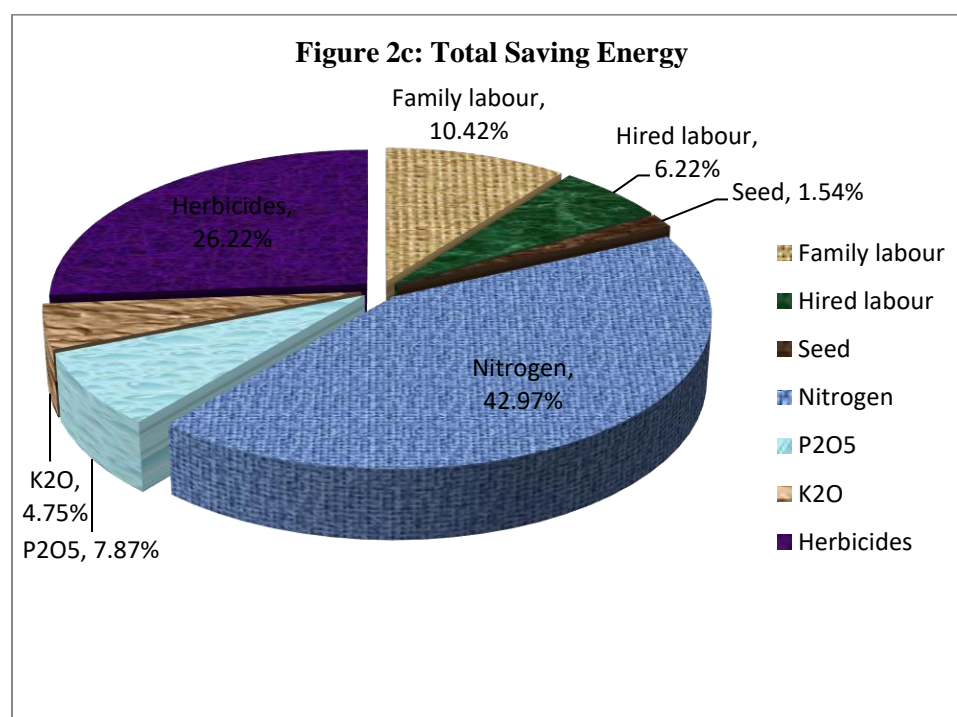
### 3.4. Setting Realistic Input Levels for Inefficient Farmers

A BCC efficiency score of less than one for a DMU indicates that, at present conditions, he is consuming more energy than required. Therefore, it becomes imperative to suggest realistic levels of energy to be used from each source for every inefficient DMU in order to avert wastage of energy. The summarized information for setting realistic input levels are given in Table (5a). It gives the average energy usage in actual condition (MJha<sup>-1</sup>), optimum conditions (MJha<sup>-1</sup>), possible energy savings (MJha<sup>-1</sup>), and ESTR percentage for different energy sources. It is evident that, total energy input could be reduced to 1588.2 MJha<sup>-1</sup>; while, maintaining the current yield level and also assuming no other constraining factors. Optimum family labour, hired labour and seeds energies were 130.89MJha<sup>-1</sup>, 88MJha<sup>-1</sup>, and 30.74MJha<sup>-1</sup>, respectively. Moreover, optimum nitrogen, P<sub>2</sub>O<sub>5</sub>, K<sub>2</sub>O and herbicides energy inputs were 736.70MJha<sup>-1</sup>, 134.93MJha<sup>-1</sup>, 81.45MJha<sup>-1</sup> and 384.99MJha<sup>-1</sup>, respectively. Furthermore, the results of ESTR revealed that if all DMUs operated efficiently, reduction in family labour, hired labour, seeds, nitrogen, P<sub>2</sub>O<sub>5</sub>, K<sub>2</sub>O, and herbicides energy inputs by 37.98%, 35.10%, 27.8%, 30.96%, 30.96%, 30.96% and 34.37% would be possible without affecting the yield level. These energy inputs had high inefficiency which was mainly due to excess use. High percentage of fertilizer (NPK), seeds and herbicides energy inputs can be attributed to price subsidies associated with them and freely availability of these inputs in the study area by politicians. Pundits opined that fertilizer policy in Nigeria is political, and this current research proved them right and justifies their submission. Accurate fertilizer management by increasing its profitability with the crops and reducing losses by improving management practices will crucially improve energy use. Furthermore, the ESTR for family labour and hired labour energy inputs are 37.98% and 35.10%, respectively; indicating that these inputs were inefficiently utilized by the respective DMUs in the study area. This outcome is not surprising because this kind of labour (former) is free of charge and in abundance, given to the fact that large household-size in traditional agriculture in African setting is synonymous with productivity, while the later kind of labour is cheap and in abundance in the study area, because agriculture (crop production) is the sole employer of labour in the study area. It is evident that during the lean season human labour becomes redundant in the study area, thus, constitutes societal threat (crimes) in the state which gives sleepless night to the law abiding citizens and law enforcement agencies (Amruta Smit Thakkar, 2015). This research scientifically proved that the current amount of human labour devoted to this crop in the study area is detrimental to production. Therefore, the researcher opines that the state government should create an enabling industrial environment, so that other sectors will absolve this wasted energy resources from human labour in agriculture, i.e, excess of this labour should be channeled into other labour demanding activities.

Moreover, the results revealed that, the ESTR percentage for total energy input was 32.62%, implying that by adopting the recommendations proffered by this study, on the average; approximately 32.62% (768.89MJha<sup>-1</sup>) from total input energy in maize production could be saved without affecting the yield level. Therefore, it is possible to advise inefficient DMUs, referencing better operating practices followed by his peers in order to reduce the input energy levels to the optimum values indicated in the analysis while achieving the present output level obtained.

Figure (2c) revealed the summarized distribution pattern of saving energy from different sources used in maize production in the study area. It is clear that the maximum contribution to the total saving energy was 37.98% from family labour. Furthermore, non-renewable energy (fertilizer, herbicides) inputs account for highest contribution to the total saving energy, approximately 81.81%, which is more than two-third (2/3) of total saving energy. This justifies the previous studies by Sadiq and Isah (2015a); Sadiq (2015); Sadiq and Isah (2015b) who reported that non-renewable energy was the greatest energy input consumed in maize production in Niger State, Nigeria; and the excessive use of these chemical energy inputs in agriculture may create serious environmental

consequences such as nitrogen loading in the environment and receiving H<sub>2</sub>O, poor H<sub>2</sub>O quality, carbon emission and contamination of the food chain. From this finding, the researcher strongly advocated that improving the usage pattern of these inputs should be considered as priorities for significant improvement in energy productivity in maize production in the study area. Improving energy use efficiency of human labour at farm level properly and adopting enterprise diversification to utilize the excess labour opportunity will curtail wastages recorded by these inefficient farmers (DMUs). Applying a better management technique, employing the conservation tillage methods and also, controlling input use by performance monitoring can help to reduce the agro-chemical energy inputs, thereby, minimizing their environmental impacts. Moreover, integrating a legume into the crop rotation, application of composts, chopped residues or other soil amendments may increase soil fertility in the medium term, thus, reduces the need for chemical fertilizer energy inputs. However, actual energy use, optimum energy use and saving energy from different sources, individual-wise are shown in Table (5b). Furthermore, Figure (2a-2b, 2d-2e) depicts individual-wise pattern of distribution of actual, optimum, saving energies, respectively, and ESTR between these DMUs using Lorenz curve in conjunction with Gini coefficient. For figure 2a & 2b, Lorenz curve depict equal distribution in actual (0.186) and optimum (0.139) energies used by the DMUs, while figure 2d visualize inequality in the distribution of saving energy among the DMUs (0.507), and this implies that the farmers exhibit wide variation in the amount of energy wasted, and this effect tends to manifest in ESTR (%) distribution among the DMUs (0.395)



**Table 5a** Energy Saving (MJha<sup>-1</sup>) from different sources if recommendations of study are followed

Input	Actual use (MJha <sup>-1</sup> )	Optimum use (MJha <sup>-1</sup> )	Energy saving (MJha <sup>-1</sup> )	ESTR (%)	Contribution to total saving energy (%)
<b>Family labour</b>	211.029	130.89	80.14	37.98	10.42
<b>Hired labour</b>	136.35	88.50	47.86	35.10	6.22
<b>Seeds</b>	42.56	30.74	11.82	27.8	1.54
<b>Nitrogen</b>	1067.12	736.70	330.42	30.96	42.97
<b>P<sub>2</sub>O<sub>5</sub></b>	195.46	134.93	60.53	30.96	7.87
<b>K<sub>2</sub>O</b>	117.98	81.45	36.53	30.96	4.75
<b>Herbicides</b>	586.57	384.99	201.59	34.37	26.23

Total | 2357.07 | 1588.20 | 768.89 | 32.62 | 100

Source: DEA result output and field survey, 2014

### 3.5. Improvement of Energy Indices

The energy indices for maize production with respect to actual and optimum energies used are given in Table (6). Making comparison between energy indices in the actual energy use and optimum energy use showed an improvement of these indices. The energy ratio estimate was 4.62 and can be improved to an estimated value of 6.85. Energy productivity, specific energy and net energy were  $0.31\text{kgMJ}^{-1}$ ,  $3.19\text{MJkg}^{-1}$  and  $8524.31\text{MJha}^{-1}$ , respectively, subsequently can be improved to estimated values of  $0.47\text{kgMJ}^{-1}$ ,  $2.15\text{MJkg}^{-1}$  and  $9293.18\text{MJha}^{-1}$ . It is evident that by optimization of energy use, both the energy ratio and energy productivity indicators can improve by 4.98% and 51.61%, respectively. Furthermore, with optimum consumption of energy inputs, the net energy indicator improvement by approximately 9.02% would give an estimated value of  $9293.18\text{MJ ha}^{-1}$ . Also specific energy can improve, while, agro-chemical energy ratio, renewable energy, non-renewable energy, commercial and non-commercial energies, respectively can decrease if inefficient DMUs (farmers) comply with the recommendations of this findings.

**Table 6** Comparison between energy indices and improved energy indices for maize production

Items	Unit	Quantity in Actual use	Quantity in Optimum use	Difference (%)
Energy ratio	-	4.62	6.85	4.98
Energy productivity	$\text{Kg MJ}^{-1}$	0.31	0.47	51.61
Specific energy	$\text{MJ Kg}^{-1}$	3.19	2.15	-32.60
Agro-chemical energy ratio	%	83.46	84.25	0.95
Direct energy <sup>a</sup>	$\text{MJ ha}^{-1}$	347.38(14.74)	219.39(13.81)	-36.84
Indirect energy <sup>b</sup>	$\text{MJ ha}^{-1}$	2009.69(85.26)	1368.81(86.19)	-31.89
Industrial energy <sup>c</sup>	$\text{MJ ha}^{-1}$	389.94(16.54)	250.13(15.75)	-35.85
Biological energy <sup>d</sup>	$\text{MJ ha}^{-1}$	1967.13(83.46)	1338.07(84.25)	-31.98
Renewable energy <sup>e</sup>	$\text{MJ ha}^{-1}$	389.94(16.54)	250.13(15.75)	-35.85
Non-renewable energy <sup>f</sup>	$\text{MJ ha}^{-1}$	1967.13(83.46)	1338.07(84.25)	-31.98
Commercial energy <sup>g</sup>	$\text{MJ ha}^{-1}$	2146.04(91.05)	1457.31(91.76)	-32.09
Non-commercial energy <sup>h</sup>	$\text{MJ ha}^{-1}$	211.029(8.95)	130.89(8.24)	-37.98
Net energy	$\text{MJ ha}^{-1}$	8524.31	9293.18	9.02
Total input energy	$\text{MJ ha}^{-1}$	2357.07	1588.20	-32.62

Source: DEA result output and field survey, 2014

( ): percentage (%)

<sup>a</sup>Human labour

<sup>b</sup>Includes seeds, fertilizers and herbicides

<sup>c</sup>Includes human labour and seeds

<sup>d</sup>Includes fertilizers and herbicides

<sup>e</sup>Includes human labour and seeds

<sup>f</sup>Includes fertilizers and herbicides

<sup>g</sup>Includes hired labour, seeds, fertilizers and herbicides

<sup>h</sup>Family labour

### Comparison of GHG emissions between efficient and inefficient farmers

GHG emission of inefficient and efficient DMUs was investigated to determine the role of energy optimization in environmental condition of maize production in the study area (Table 7). Results revealed the GHG emissions of overall inefficient and 5 most efficient farmers were  $29.47\text{ kgCO}_2\text{eq}$  and  $24.30\text{ kg CO}_2\text{eq ha}^{-1}$ , respectively. As it can be seen, the total GHG emission of inefficient units was more than GHG emission of efficient farmers by approximately 17.54 percent. The highest difference between inefficient and efficient units was observed in Herbicides (21.14%). Therefore, herbicides consumption of inefficient units should be close to

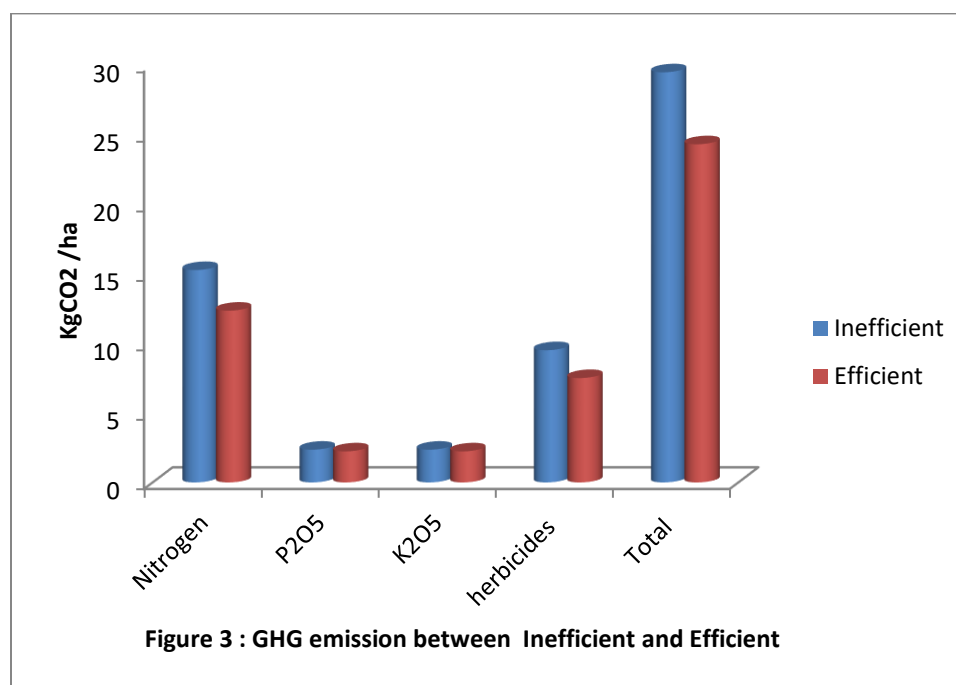
that of most efficient ones. For this purpose, the use of dose recommended by finding is the best solution. Also, applying cultural and biological controls are major solution to reduction of biocide and chemical fertilizers.

**Table 7** Comparison of GHG emissions between efficient and inefficient farmers

Input	Inefficient (KgCO <sub>2</sub> ha <sup>-1</sup> ) (A)	Efficient (KgCO <sub>2</sub> ha <sup>-1</sup> ) (B)	Difference [(A-B)/A]*100
<b>Nitrogen</b>	15.262	12.34	19.15
<b>P<sub>2</sub>O<sub>5</sub></b>	2.348	2.23	5.03
<b>K<sub>2</sub>O</b>	2.35	2.23	5.12
<b>Herbicides</b>	9.51	7.50	21.14
<b>Total</b>	29.47	24.30	17.54

Source: Computation from DEAP 2.1 computer print-out

Figure 3 displays the amount of each input for inefficient and efficient units from GHG emissions point of view. Results indicate GHG emission from biocides (herbicides) to be the highest; followed by Nitrogen fertilizer, potassium fertilizer and lastly phosphorus fertilizer. It can be observed, that biocides and Nitrogen fertilizer consumption of inefficient units were more than that of efficient units. Though, virtually all estimates of the main inputs of GHG creator for inefficient and efficient farmers' were relatively far apart. Specifically, the researchers opined that consumption of biocides (herbicides) and Nitrogen fertilizer should be reduced in all units.



#### 4. CONCLUSION

Maize is a crop with relatively high requirements for nonrenewable energy resources; its fertilizer energy requirement is high and it needs high amount of herbicides consumption. Most of these farmers (DMUs) don't have enough knowledge on efficient input usage and there common belief is increased use of energy resources will increase their yield. The methodologies presented in this research demonstrate how energy use efficiency in maize production will improve by applying the operational management tools to assess the performance of the DMUs (farmers). Agro-chemical and human labour energies were inconsistent with output, indicating, the use of these inputs are high, resulting in energy dissipation as well as imposing negative effects to environment and human health. Energy utilized among the inefficient farmers was observed to be higher than energy consumed by efficient farmers, despite facing the same technology. However, substantial production inefficiencies among these farmers can be minimized by approximately 32.98% potential reduction in total energy input used if all inefficient farmers operate efficiently and assume no other constraints on this adjustment. Comparative results of GHG emissions for efficient farmers and inefficient farmers revealed that the

amount of CO<sub>2</sub> emissions in efficient DMUs was less than inefficient DMUs. Without doubt, maize 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.

Researchers advise governmental and non-governmental agricultural institutes in the state to key into the nascent world advocate of establishing and enhancing energy efficiency, aimed at mitigating climate change effects due to GHG emission from agricultural activities.

**Table 3b** Individual-wise statistics for the three measures of efficiency

DMUs (farmers)	CCR	BCC	Scale efficiency	RTS	TFP index	DMUs (farmers)	CCR	BCC	Scale efficiency	RTS	TFP index
MF01	0.71	0.880	0.809	IRS	1.00	MF31	0.696	0.709	0.981	IRS	0.9625
MF02	1	1.000	1.00	CRS	1.8068	MF32	0.366	0.403	0.908	IRS	0.4627
MF03	0.613	0.925	0.662	IRS	0.8254	MF33	0.519	0.586	0.884	IRS	0.7646
MF04	0.56 2	0.617	0.912	IRS	0.7481	MF34	0.698	0.727	0.960	IRS	0.9107
MF05	0.692	0.835	0.828	IRS	0.842	MF35	0.904	0.979	0.924	IRS	0.8999
MF06	0.675	0.814	0.828	IRS	0.9591	MF36	0.694	0.858	0.810	IRS	0.9412
MF07	0.758	1.000	0.758	IRS	1.0206	MF37	1.000	1.00	1.00	CRS	1.55
MF08	0.646	0.884	0.731	IRS	0.84662	MF38	0.738	0.750	0.985	IRS	0.9718
MF09	0.984	1.000	0.984	IRS	1.2482	MF39	0.397	0.410	0.968	IRS	0.5164
MF10	0.422	0.518	0.815	IRS	0.562	MF40	0.824	0.910	0.906	IRS	1.1826
MF11	0.622	0.633	0.982	IRS	0.8018	MF41	0.777	0.847	0.917	IRS	0.8454
MF12	0.367	0.497	0.739	IRS	0.2655	MF42	0.622	0.642	0.969	IRS	0.894
MF13	0.385	0.546	0.704	IRS	0.3175	MF43	0.792	0.902	0.879	IRS	1.2318
MF14	0.804	1.000	0.804	IRS	1.1439	MF44	0.489	1.00	0.489	IRS	0.7401
MF15	0.394	0.460	0.856	IRS	0.5057	MF45	0.813	0.822	0.989	IRS	0.985
MF16	0.625	0.69	0.906	IRS	0.7167	MF46	0.635	0.649	0.978	DRS	0.8438
MF17	0.489	0.532	0.921	IRS	0.7204	MF47	0.489	0.528	0.926	IRS	0.731
MF18	0.329`	0.344	0.958	IRS	0.483	MF48	0.590	0.706	0.835	IRS	0.8319
MF19	0.870	0.923	0.942	IRS	1.2362	MF49	0.477	0.542	0.881	IRS	0.715
MF20	0.588	0.776	0.757	IRS	0.8393	MF50	0.538	0.612	0.879	IRS	0.7417
MF21	0.597	0.64	0.933	IRS	0.8537	MF51	0.453	0.462	0.980	IRS	0.6633
MF22	0.714	0.85	0.840	IRS	0.94	MF52	0.946	1.00	0.946	DRS	1.4539
MF23	0.556	0.614	0.905	IRS	0.807	MF53	0.614	0.624	0.983	IRS	0.89
MF24	0.730	0.911	0.802	IRS	0.9458	MF54	0.805	0.853	0.944	IRS	0.9593
MF25	0.354	0.394	0.899	IRS	0.4543	MF55	0.653	0.689	0.948	IRS	0.8343
MF26	0.628	0.666	0.943	IRS	0.8793	MF56	0.516	0.572	0.901	IRS	0.7807
MF27	0.700	0.717	0.977	IRS	0.9697	MF57	1.00	1.00	1.00	CRS	1.2163
MF28	0.741	0.982	0.754	DRS	1.0534	MF58	0.494	0.621	0.796	IRS	0.678
MF29	0.654	0.673	0.973	IRS	0.9039	MF59	0.647	0.861	0.752	IRS	0.881
MF30	0.872	0.962	0.907	IRS	1.1594	MF60	0.580	0.708	0.818	IRS	0.8273

DMUs (farmers)	CCR	BCC	Scale efficiency	RTS	TFP index	DMUs (farmers)	CCR	BCC	Scale efficiency	RTS	TFP index
MF61	0.429	0.436	0.984	DRS	0.6056	MF94	0.864	1.00	0.864	IRS	1.1959
MF62	0.684	0.737	0.928	DRS	0.7731	MF95	0.500	0.522	0.956	DRS	0.7609
MF63	0.834	0.854	0.976	DRS	1.2499	MF96	0.225	1.00	0.225	IRS	0.3615
MF64	0.978	0.993	0.985	DRS	1.1702	MF97	0.779	1.00	0.779	IRS	0.7246
MF65	0.740	0.747	0.992	IRS	1.0848	MF98	0.437	1.00	0.437	IRS	0.4917
MF66	0.576	0.824	0.699	DRS	0.7086	MF99	0.489	0.508	0.961	IRS	0.7823
MF67	0.738	0.761	0.970	IRS	1.0011	MF100	0.679	0.810	0.838	IRS	1.0095
MF68	0.741	0.982	0.754	DRS	1.0744	MF101	0.612	0.627	0.976	IRS	0.9329
MF69	0.758	0.768	0.987	IRS	0.9849	MF102	0.447	0.597	0.748	IRS	0.7308
MF70	0.741	0.982	0.754	DRS	1.0363	MF103	0.587	0.736	0.798	IRS	0.8262
MF71	0.739	0.825	0.896	IRS	0.8291	MF104	0.755	0.788	0.958	IRS	1.0987
MF72	0.674	0.688	0.980	IRS	0.9661	MF105	0.718	0.878	0.818	IRS	0.9859
MF73	0.741	0.982	0.754	DRS	1.1028	MF106	0.619	1.00	0.619	IRS	0.8322
MF74	1.00	1.00	1.00	CRS	1.007	MF107	0.635	0.871	0.729	IRS	0.5964
MF75	0.739	0.836	0.883	IRS	1.0401	MF108	0.893	0.919	0.972	IRS	0.7001
MF76	0.490	0.774	0.634	IRS	0.6882	MF109	0.800	1.00	0.800	IRS	0.9415
MF77	1.00	1.00	1.00	CRS	1.5985	MF110	0.670	0.900	0.744	IRS	1.0323
MF78	0.606	0.745	0.814	IRS	0.5744	MF111	0.626	0.700	0.895	IRS	0.9474
MF79	0.800	0.871	0.918	DRS	1.2088	MF112	0.835	0.895	0.933	IRS	1.0979
MF80	0.519	0.612	0.848	DRS	0.7882	MF113	1.00	1.00	1.00	CRS	1.1714
MF81	0.871	0.894	0.974	IRS	1.2693	MF114	0.619	1.00	0.619	IRS	0.8035
MF82	0.628	0.640	0.981	DRS	0.887	MF115	0.650	0.857	0.758	IRS	0.9632
MF83	1.00	1.00	1.00	CRS	0.8439	MF116	0.605	0.611	0.991	IRS	0.9625
MF84	1.00	1.00	1.00	CRS	1.0247	MF117	0.686	0.769	0.892	IRS	1.0875
MF85	0.873	0.923	0.946	IRS	0.7863	MF118	0.970	0.975	0.995	DRS	1.1708
MF86	0.537	0.553	0.972	DRS	0.6099	MF119	0.773	0.778	0.994	IRS	1.1299
MF87	1.00	1.00	1.00	CRS	1.1503	MF120	0.604	0.620	0.973	IRS	0.9436
MF88	1.00	1.00	1.00	CRS	1.5306						
MF89	1.00	1.00	1.00	CRS	1.4825						
MF90	0.689	1.00	0.689	IRS	1.0226						
MF91	0.752	0.757	0.993	IRS	1.1437						
MF92	0.683	0.713	0.958	DRS	1.0674						
MF93	0.584	0.599	0.975	DRS	0.9468						

**Table 5b** Individual-wise distribution of actual energy, optimum energy, energy saving, ESTR and GHG emission

DMUs (farmers)	Actual (MJha <sup>-1</sup> )	Optimum (MJha <sup>-1</sup> )	Energy saving	ESTR (%)	GHG emission (kg CO <sub>2</sub> )	DMUs (farmers)	Actual (MJha <sup>-1</sup> )	Optimum (MJha <sup>-1</sup> )	Energy saving	ESTR (%)	GHG emission (kg CO <sub>2</sub> )
MF01	1612.45	1270.169	342.281	21.227	222.823	MF33	2086.8	1155.606	931.194	44.623	119.101
MF02	1354.71	1354.71	0	0	33.1	MF34	1853.8	1342.071	511.729	27.604	89.858
MF03	2059.09	1296.246	762.844	37.048	587.683	MF35	1751.31	1315.462	435.848	24.887	45.919
MF04	2255.64	1334.546	921.094	40.835	247.643	MF36	1820.48	1383.875	436.605	23.983	66.344
MF05	1641	1338.342	302.658	18.444	128.405	MF37	1222.69	1222.69	0	0	33.1
MF06	1649.45	1277.551	371.899	22.547	185.186	MF38	1851.84	1360.591	491.249	26.528	85.602
MF07	1337.1	1322.21	14.89	1.114	33.1	MF39	3692.88	1352.438	2340.442	63.377	301.644
MF08	1736.54	1271.819	464.721	26.761	300.186	MF40	1346.24	1201.935	144.305	10.719	51.088
MF09	1322.21	1322.21	0	0	33.1	MF41	1900.83	1325.956	574.874	30.243	92.886
MF10	2450.24	1152.593	1297.647	52.96	235.919	MF42	1980.64	1266.611	714.029	36.050	145.643
MF11	2578	1790.581	1057.419	41.017	265.988	MF43	1312.29	1181.863	130.427	9.939	62.604
MF12	5759.28	1472.075	4287.205	74.440	799.971	MF44	1172.21	1172.21	0	0	33.1
MF13	4531.2	1521.928	3009.272	66.412	916.831	MF45	1839.84	1460.332	379.508	20.627	71.003
MF14	1300.25	1300.25	0	0	33.1	MF46	2461.59	1418.047	1043.543	42.393	138.009
MF15	2899.13	1179.484	1719.646	59.316	375.35	MF47	2364	1194.227	1169.773	49.483	231.673
MF16	2570.64	1599.711	970.929	37.770	229.648	MF48	1984.88	1344.112	640.768	32.283	94.141
MF17	2395.72	1271.074	1124.646	46.944	330.049	MF49	2402.08	1204.559	1197.521	49.854	409.029
MF18	4531.84	1321.052	3210.788	70.850	930.032	MF50	2569.52	1335.327	1234.193	48.032	559.653
MF19	1457.99	1338.765	119.225	8.177	64.568	MF51	3187.28	1293.624	1893.656	59.413	706.997
MF20	1667.33	1222.773	44.557	26.663	186.571	MF52	2808.16	2808.16	0	0	33.1
MF21	2683.2	1469.319	1213.881	45.240	509.007	MF53	2735.32	1576.288	1159.032	42.373	508.761
MF22	1814.6	1360.235	454.365	25.040	67.991	MF54	2497.5	2030.746	466.754	18.689	240.503
MF23	2016.24	1174.994	841.246	41.724	113.358	MF55	2038.64	1335.858	702.782	34.473	165.542
MF24	1808.72	1418.46	390.26	21.577	56.371	MF56	2286.76	1285.46	1000.9	43.769	258.68
MF25	3462.72	1157.236	2305.484	66.580	180.24	MF57	1689.76	1689.76	0	0	33.1
MF26	1889.08	1242.062	647.018	34.250	102.649	MF58	2476.56	1317.841	1158.719	46.787	365.867
MF27	1855.76	1266.946	588.814	31.729	93.169	MF59	2346.67	1956.244	390.426	16.638	188.621
MF28	2148.56	1821.057	326.603	15.201	36.727	MF60	2573.12	1575.547	997.573	38.769	467.421
MF29	2051.52	1261.603	789.917	38.504	101.221	MF61	4527.92	1788.077	2739.843	60.510	764.995
MF30	1322.72	1255.636	67.084	5.072	40.752	MF62	4340.24	2557.274	1782.966	41.080	332.338
MF31	1871.44	1319.625	551.815	29.486	93.530	MF63	2682.96	2284.588	398.372	14.848	156.403
MF32	3435.28	1152.396	2282.911	66.455	178.697	MF64	2127.24	2089.957	37.283	1.753	37.112

DMUs (farmers)	Actual (MJha <sup>-1</sup> )	Optimum (MJha <sup>-1</sup> )	Energy saving	ESTR (%)	GHG emission (kg CO <sub>2</sub> )	DMUs (farmers)	Actual (MJha <sup>-1</sup> )	Optimum (MJha <sup>-1</sup> )	Energy saving	ESTR (%)	GHG emission (kg CO <sub>2</sub> )
MF65	2493.64	1858.657	634.983	25.464	220.778	MF94	1883.28	1883.28	0	0	33.1
MF66	3261.24	1874.063	1387.177	42.535	89.026	MF95	4339.76	2183.333	2156.427	49.690	613.857
MF67	1832.24	1242.186	590.054	32.204	85.958	MF96	948.72	948.72	0	0	33.1
MF68	2122.08	1821.957	300.123	14.143	36.727	MF97	2107.16	2107.16	0	0	33.1
MF69	1847.92	1395.379	452.541	24.489	81.810	MF98	967.67	967.67	0	0	33.1
MF70	2173.04	1821.957	351.083	16.156	36.727	MF99	2792.48	1388.281	1404.199	50.285	449.476
MF71	1790.51	1277.46	513.05	28.654	73.768	MF100	2216.44	1753.009	463.431	20.909	133.081
MF72	1877.32	1283.716	593.604	31.620	98.018	MF101	2628.08	1647.715	980.365	37.305	348.698
MF73	2094.64	1821.957	272.683	13.018	36.727	MF102	2044.24	1180.824	863.416	42.237	264.709
MF74	1802.84	1802.84	0	0	33.1	MF103	2512.44	1679.684	832.756	337.871	409.904
MF75	1845.96	1431.677	414.283	22.443	69.293	MF104	2281.04	1514.323	766.717	347.221	421.386
MF76	1923.8	1410.052	513.748	26.705	105.785	MF105	2483.28	1922.393	560.887	22.587	366.964

MF77	1189.52	1189.52	0	0	33.1	MF106	2279.4	2003.546	275.854	12.102	190.335
MF78	3268.6	1558.776	1709.824	52.311	139.388	MF107	3930.24	1800.275	2129.965	54.194	576.635
MF79	2394.96	1836.472	558.488	23.319	328.694	MF108	3665.44	1954.917	1710.523	46.666	93.663
MF80	4164.48	2544.576	1619.904	38.900	372.548	MF109	1994.6	1994.6	0	0	33.1
MF81	1824.32	1617.386	206.934	11.343	89.380	MF110	1462.72	1253.986	208.734	14.270	87.025
MF82	2726.96	1613.236	1113.724	40.841	261.202	MF111	2006.01	1316.778	689.232	34.358	220.721
MF83	2504.45	2504.45	0	0	33.1	MF112	2683.2	1869.724	813.476	30.317	450.505
MF84	3516.96	3516.96	0	0	33.1	MF113	2052.04	2052.04	0	0	33.1
MF85	4008.64	2243.703	1764.937	44.028	534.383	MF114	2771.08	2011.68	759.4	27.405	565.67
MF86	3467.12	1466.685	2000.435	57.697	146.824	MF115	2311.44	1957.163	354.277	15.327	132.406
MF87	2412	2412	0	0	33.1	MF116	2683.2	1471.117	1212.083	45.173	504.032
MF88	2011.68	2611.68	0	0	33.1	MF117	1812.1	1356.005	456.095	25.169	140.859
MF89	2906	2906	0	0	33.1	MF118	2440.16	2023.042	417.118	17.094	367.329
MF90	1937.3	1937.3	0	0	33.1	MF119	2620.96	1550.068	1070.892	40.859	616.266
MF91	2248.28	1696.033	552.247	24.563	166.284	MF120	2180.39	1351.211	829.179	38.029	232.933
MF92	2832.16	1963.484	868.935	30.681	275.875						
MF93	2870.88	1693.484	1177.396	41.0117	377.795						

Figure 1b: CCR (Overall Technical Efficiency)

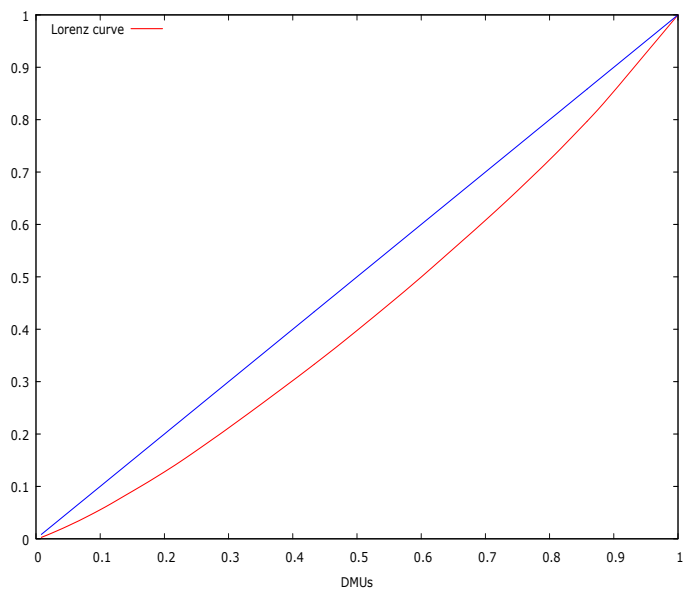


Figure 1c: BCC (Pure Technical Efficiency)

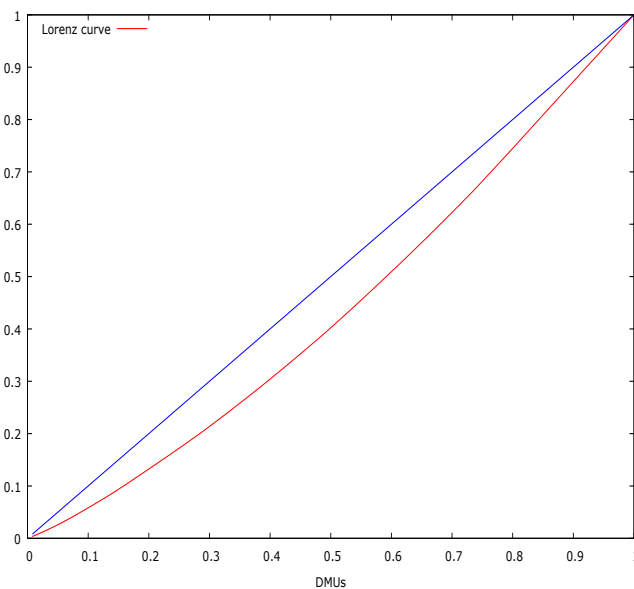
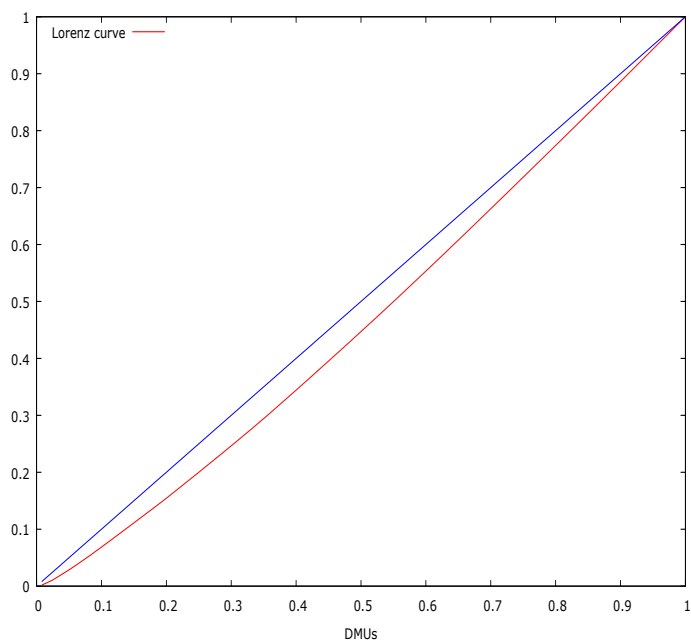


Figure 1d: Scale Efficiency



Measure	CCR	BCC	Scale Efficiency
Sample Gini coefficient	0.146	0.129	0.0738
Pop. Gini coefficient	0.147	0.131	0.0744

Figure 1f: Total Factor Productivity (TFP)

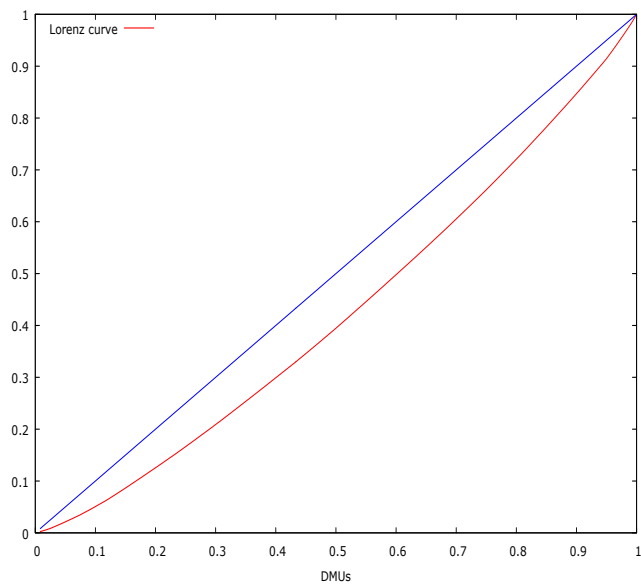


Figure 2a: Actual Energy (MJ/ha)

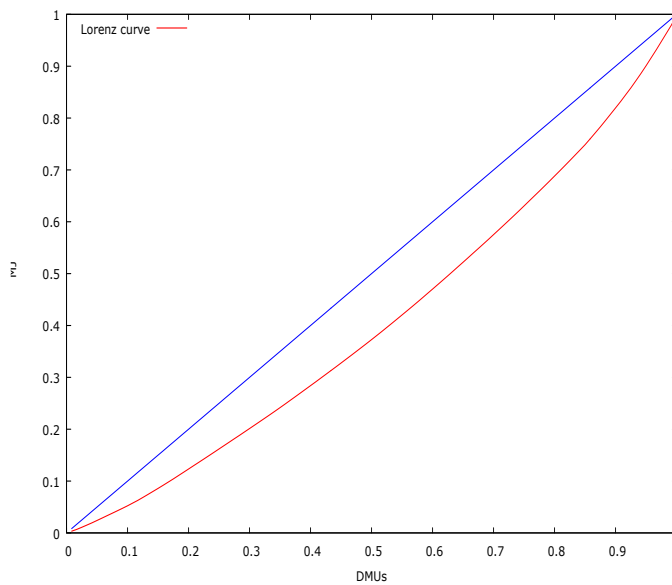
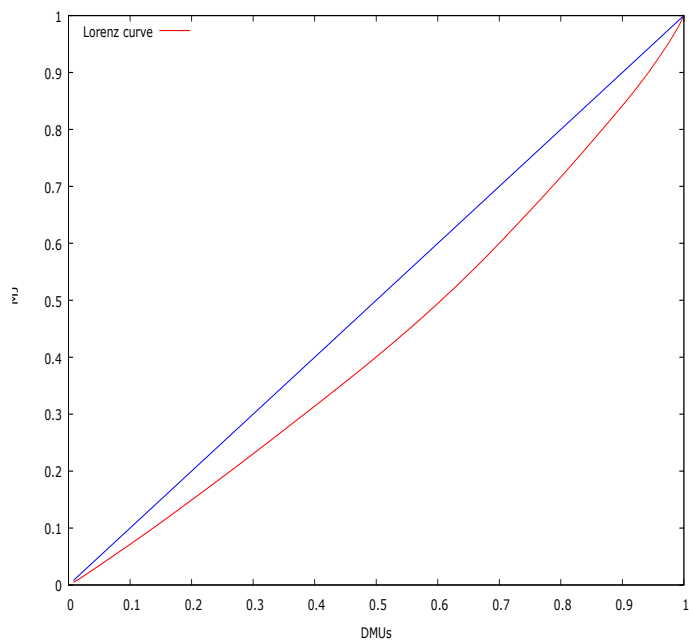


Figure 2b: Optimum Energy (MJ/ha)



Measure	TFP	Actual Energy	Optimum Energy
Sample Gini coefficient	0.153	0.186	0.139
Pop. Gini coefficient	0.154	0.187	0.140

Figure 2d: Saving energy

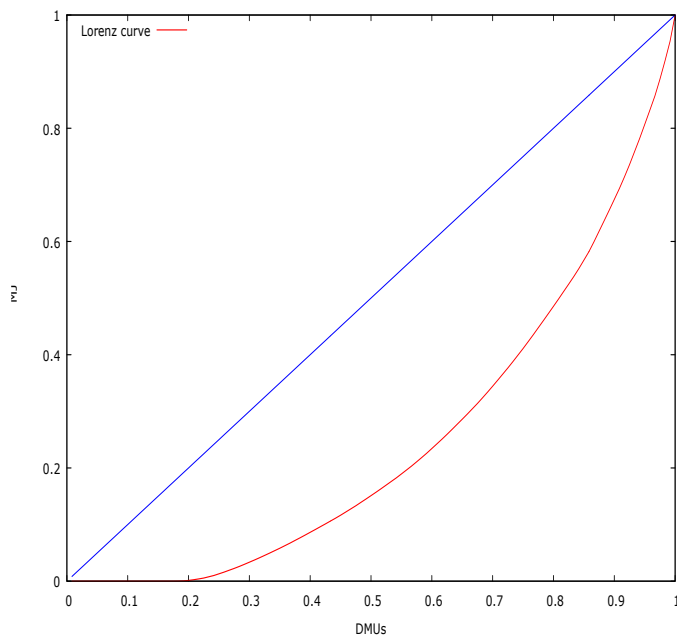


Figure 2e: ESTR

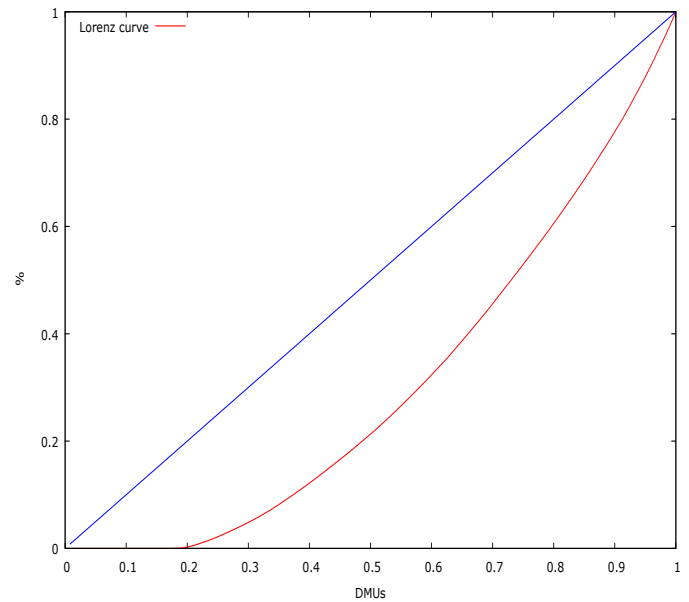
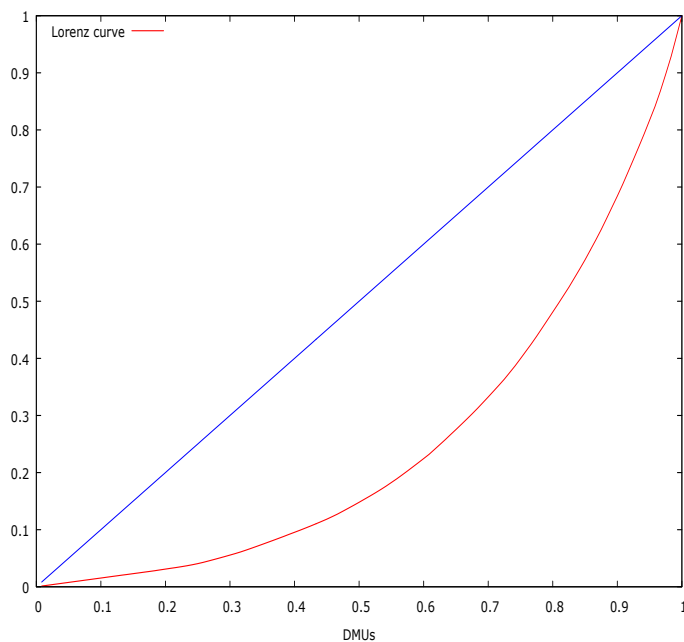


Figure 3b: GHG emission



Measure	Saving energy	ESTR (%)	GHG (kg CO <sub>2</sub> )
Sample Gini coefficient	0.507	0.395	0.494
Pop. Gini coefficient	0.511	0.398	0.498

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