Technical efficiency and technology gap ratios among rice farmers in Kenya

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Abstract:

Rice farming remains an important undertaking in Asia and Africa due to its important role in maintaining essential food supply. Rice ranks second to maize in providing more than one-fifth of the calories consumed worldwide. In Kenya, rice is an important food crop and cash crop. A survey of 773 farmers was undertaken in Mwea, West Kano, Ahero and Bunyala rice growing regions to investigate the technical efficiency and technology gap ratios. The meta-frontier estimates indicate that the technical efficiency of Mwea, West Kano, Ahero and Bunyala was 0.556, 0.475, 0.402 and 0.45 respectively. The regional efficiencies indicate that the technical efficiency of Mwea, WestKano, Ahero and Bunyala was 0.557, 0.784, 0.833 and 0.937 respectively. Thus, the technology gap ratio was 0.998, 0.605, 0.482 and 0.48 for Mwea, West Kano, Ahero and Bunyala respectively. The results thus suggest that a narrow gap existed between the region and the meta-frontier results for Mwea, while a wider gap existed for West Kano, Ahero and Bunyala implying that Mwea farmers were more technically efficient than farmers in the other schemes. Using the fractional regression models the determinants of efficiency were found to be age, farmer's gender, humidity, rainfall, temperature and adopting technologies.

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Key words: *technical efficiency, technology gap ratios, determinants*

Introduction

The global population now at 7 billion is still growing rapidly and is projected to reach 9 billion by 2050, and increasing incomes and urbanization will inevitably lead to dietary change. The food security challenge will increasingly encompass the triple burden of malnutrition-undernutrition, obesity and micronutrient deficiencies especially in developing countries where food production is being constrained by low productivity. In recent times, significant emphasis and substantial resources have been focussed on increasing food production in many countries (Nagothu, 2014; Wei et al., 2009; Wilson et al., 2013). In countries where food insecurity is rampant, the policy-makers aim to improve productivity by turning the root causes of chronic food insecurity into priority objectives for development. Kenya's hunger level is rated as "serious" placing it ahead of countries such as Pakistan and Iraq despite Kenya ranking as one of the largest and fast-growing economies in the Eastern and Central African region. Over ten million Kenyans suffer from chronic food insecurity and a further 1.8 million children are classified as chronically undernourished. In addition, between two and four million people every year are in dire need of food relief (GoK, 2011). Due to the hunger concern, the right to food is now articulated in Article 43 (c) of Kenya's constitution of 2010 which states that "*each individual has the right to be free from hunger and to have adequate food of an acceptable quality*" (Constitution of Kenya, 2010).

Rice is one of the crops earmarked worldwide as a food security crop that is capable of reducing the number of gravely food insecure people since the World Food Summit of 1996 and is being promoted in many African countries. Rice farming is an important concern in many countries both in Asia and Africa because of its important role in maintaining domestic food security and as well as improving agricultural development (Bishwajit et al., 2013; Enwerem & Ohajianya, 2013; Heriqbaldi, Purwono, Haryanto, & Primanthi, 2014; Kadiri et al., 2014; Khai & Yabe, 2011; Mushtaq, Maraseni, Maroulis, & Hafeez, 2009).

Globally, rice is one of the most important food crops and ranks second only to maize in terms of total volume of production providing more than one fifth of the calories consumed worldwide by human beings (Dawe, Pandey, & Nelson, 2010). Rice consumption continues to rise steadily in sub-Saharan Africa where the increase has been by more than 50%. Further increase in demand has been projected in many African countries, for example, in Central and Eastern Africa high population growth and increased purchasing power associated with rapid increases in income is expected to increase demand for rice by about 300% between 2010 and 2050. Instructively, rice demand in both regions is still expected to double if income growth is more limited but population growth occurs at a more rapid rate (Zuberi & Thomas, 2012). It is projected that 112 million tons of additional rice will be needed globally by 2040 and nearly 40% of this additional demand will be coming from Africa. Hence unless rice production in Africa keeps pace with its rising consumption, then the continent is likely to emerge as a growing importer of rice from Asia (Mohanty, 2013). Despite the importance of this crop, rice remains a political commodity since in most cases the government is a major player in the development of the rice infrastructure such as irrigation facilities, input supplies, credit or the market function. Thus, as a result government policies can have a major bearing on the incentive an individual farmer or miller has for increasing production.

Rice is one important crop that has attained a staple food status in Kenya and also become a source of calories for the urban people. Rice is 3rd after maize and wheat in order of economic importance among cereals in Kenya. Annual demand for rice in Kenya has been growing much more rapidly than production, at an average rate of 11 percent per year between 1963 and 2013. The estimated rice production is at 325,000 tons which exceeds the national rice production currently estimated at 110,000 tons by about 200%. This huge gap between consumption and production is met through imports which costs the country millions of dollars (GoK, 2010). Kenya's rice import dependency ratio for the decade remains high, at more than 80% which means local production only meets about 20% of the demand. Kenya imports nearly all of its rice from the East Asia, with Pakistan accounting for 74% of total rice imports during the period 2006-2013. Kenya has set a target of increasing rice production to 178,580 MT/year by 2018 as set out in its National Rice Development Strategy (NRDS) in order to stabilize the rice consumption. The specific strategies as spelled out in the plan include the use of quality inputs especially seeds, deploy extension officers in rice growing areas, mechanization and post-harvest technology improvement among others.

This paper has two major objectives, first it will quantify the technical efficiency of rice farming sector of Kenya and second it will identify the determinants of efficiency. Since the Kenyan market heavily relies on rice imports, analysis of efficiency becomes important since it will help the farmers to identify and eliminate their source of inefficiency hence become more efficient. This research will help identify incentives and policies that could lead to the adoption of sustainable rice farming practices.

The rest of the paper is organized as follows. A review of existing studies is outlined in section 2. A summary of the methods used and the data sources is presented in section 3. The results are presented in section 4. Section 5 concludes the paper and draws some policy implications.

2.0 Literature on rice processing

There exists a significant number of studies in the literature focusing on technical and allocative efficiency of various crops in different regions or countries (Gebregziabher et al., 2012; Iraizoz et al., 2003; Latruffe, et al., 2004; Sekhon et al., 2010; Wadud, 2003). Studies on rice farming efficiency that exist in the literature include the analysis of rice production in the Philippines (Pate & Cruz, 2007; Yao & Shively, 2007 and Villano & Fleming, 2006). Khai and Yabe (2011) examined rice farming in Vietnam while Tian & Wan (2000) have examined the technical efficiency of grain (rice, wheat and corn) production and its determinants in China. Coelli et.al. (2002) examined the efficiency (technical, allocative, cost and scale) of 406 rice farms in 21 villages of Bangladesh for the year 1997 and found a difference in mean efficiency results between the dry (Boro) and wet (Aman) seasons. Chang & Wen (2011) analysed the technical efficiency and production risk for two categories of rice farmers in Taiwan i.e. those with off-farm work and those without off-farm work and found differences in resource use among the two categories of rice farmers. The authors found that the farmers with off-farm work faced a higher production risk than those without off-farm income and that off farm income reduced inefficiency among the lower percentiles farmers.

Although several studies on agriculture technical efficiency at the micro-level exist for Kenya (see Seyoum et al., 1998; Mochebelele & Winter, 2002), the bulk of these studies have been limited to a sample of farms mostly in the high potential zones and of dairy farmers. A few studies on rice farming in Kenya exist, mainly focusing on specific regions. For example, Omondi and Shikuku (2013) used the Cobb Douglas production function to evaluate Ahero irrigation scheme's rice farming efficiency for 220 rice farmers and found the average technical efficiency to be 0.82. The authors established that the gender of the rice farmer, rice farming experience, the farmer's income levels and market distance significantly affected efficiency. Mati et al. (2011) and Nyamai et al. (2012) evaluated the impact of adopting the system of rice intensification (SRI) among the rice farmers at the Mwea Irrigation Scheme. They found that the SRI had more benefits than the conventional method of rice growing, since it saved on water, seed, fertiliser and pesticides use, hence cutting rice farming costs. Gitau et al. (2011) evaluated Kenya's trade and agriculture competitiveness in wheat and rice, and found inefficiencies along the rice chain which included: high labour costs, high migration rate and high fertiliser/seed costs. Kuria et al. (2003) examined Mwea's rice farming efficiency by comparing one-season and two-season rice producers and found that farmers growing a single crop of rice annually to be more efficient than those growing a double crop.

The above review indicates that the studies fail to provide an in-depth analysis of Kenya's rice farming system and of the factors that determine the efficiency levels. Rice in Kenya is cultivated under diverse agroecological conditions, which means farmers face different production technologies and opportunities, and therefore may make decisions based on the input-output level choices they make (O'Donnell et al., 2008). Hence, the assumption that farmers use the same technology can lead to biased results and that unobserved differences in production techniques may be inappropriately labelled as technical inefficiency (Villano et al., 2010; Jiang & Sharp, 2015). Currently, no study exists on the technical efficiency across the rice agro-ecological zones of Kenya, a gap that this study attempts to fill. To do so, the study examines rice farming efficiencies (technical, cost and allocative) and the technology gaps across four rice agro-ecological zones of Kenya, i.e., Mwea, Ahero, West Kano and Bunyala irrigation schemes and investigates the factors that determine the efficiency levels.

3.0 Methodology

3.1: Data Envelopment Analysis

Data envelopment analysis (DEA) is a linear programming based technique for measuring the relative performance of Decision Making Units (DMUs). DEA technique was originally developed by Charnes, Cooper, and Rhodes (1978) for the purpose of evaluating performance of non-profit and public sector organizations. DEA has been accepted as a major frontier technique for benchmarking many sectors such as energy (Abbott, 2006; Jamasb & Pollitt, 2000); education (Abbott & Doucouliagos, 2003); banking (Vassiloglou & Giokas, 1990); hospitals (Puig-Junoy, 2000); among others. Though DEA has a disadvantage of exaggerating the noise component, one main advantage is that does not require a functional form and can accommodation multiple outputs. In DEA, the input or output oriented models may be used. The input-oriented approach to technical efficiency estimates to what extent a DMU could reduce the resources employed and still produce the same output level. This represents the DMU's resource intensity relative to best practice. The output-oriented DEA determines to what extent a DMU could increase its output level while employing the same level of resources. A DMU is considered efficient if it is on the best practice frontier and inefficient if vice versa. The linear programme solved for the ith firm/farm when using the output-oriented approach, can be represented as follows;

$Max\Phi_1$

Subject to:

$\Phi_1 y_{k,m} \leq \sum_{k=1}^{K} Z_k\, y_{k,m}$ $\quad \forall m \quad$ (1)

$\sum_{k=1}^{K} Z_k\, x_{k,n} \leq x_{k,n}$ $\quad n \in \alpha \quad$ (2)

$\sum_{k=1}^{K} Z_k \, x_{k,m} = \lambda_{k,n} x_{k,n}$ $\quad n \in \hat{\alpha}$ (3)

$\lambda_{k,n} \geq 0$ $\quad n \in \hat{\alpha}$ (4)

where Φ denotes a scalar showing by how much the firms can increase output; $y_{k,m}$ denotes the output *m* by farm/firm *k*; $x_{k,n}$ denotes the input *n* used by farm/firm *k* and z_k are weighting factors. Inputs comprise of fixed factors and variable factors defined by the set as $\hat{\alpha}$. To calculate the capacity output measure, relaxing of the bounds on the sub-vector of variable inputs $x_{\hat{\alpha}}$ is required. Relaxing the bounds on the sub-vector is achieved by allowing the inputs to remain unconstrained through introducing a measure of the input utilising rate ($\lambda_{k,n}$), estimated in the model for each firm *k* and variable input *n* (Färe et al., 1994). The technically efficient capacity utilisation (TECU) based on observed output (u) becomes:

$$TECU = \frac{y}{y^*} = \frac{y}{\phi_1 y} = \frac{1}{\phi_1} \quad (5)$$

where y* denotes the capacity-output based on observed outputs y. The TECU measure ranges from zero to one, with one implying full capacity utilisation (i.e. 100% of capacity) which assumes efficient use of all the inputs exists at their optimal capacity. Efficiency measures of less than one indicates that the firm operates at less than full capacity given the set of fixed inputs.

3.2 Meta-frontier analysis

The concept of measuring efficiency using meta-frontier was first developed by Hayami and Ruttan (1970), and extended by Rao et al. (2003). The meta-frontier evaluates the efficiency of firms/units that operate under different production technologies or physical environment (climate, soil type and farming history). Several studies employ the meta-frontier to evaluate technical efficiency and establish if there any technological gaps among firms operating under different production technologies in areas such as manufacturing (Rao et al., 2003; Battese et al., 2004); agriculture (Rao et al., 2008); tourism (Assaf et al., 2010) and environment (Yang, 2010; Oh, 2010; Sala-Garrido et al., 2011).

The meta-technology as defined by Rao et al. (2003) is the total of the regional technologies. For example, if some output denoted by y, can be produced using an input quantity x in any given region, then x, y will belong to the meta-technology denoted as T^*. The meta-technology then will be expressed as follows:

$T^* = ((\mathrm{x}, \mathrm{y})\colon \mathrm{x} \geq 0$ and $\mathrm{y} \geq 0$, such that x inputs will yield y outputs using at least one region specific technology, $T^1, T^2, \ldots\ldots\ldots\ldots, T^K)$ (6)

The meta-technology is assumed to satisfy all the production axioms and the convexity axiom, expressed as the convex hull of the pooled region-specific technologies as follows:

$T^* \equiv$ Convex Hull $(T^1 \cup \ldots\ldots T^2 \cup \ldots \cup T^K)$. (7)

If the input-output distance function is known such that $D_0^*(\mathrm{x}, \mathrm{y})$ and $D_i^*(\mathrm{x}, \mathrm{y})$ denote for the output and input functions respectively using the meta-technology T^*then the results of any given region should be as follows:

$D_0^k(\mathrm{x}, \mathrm{y}) \geq D_0^*(\mathrm{x}, \mathrm{y}), \mathrm{k} = 1, 2, \ldots\ldots\ldots \mathrm{K})$ and $D_i^k(\mathrm{x}, \mathrm{y}) \leq$ and $D_i^*(\mathrm{x}, \mathrm{y})$. (8)

Thus, the output oriented technology gap ratio between the region k technology and the meta-technology is computed as follows:

$$TGR_0^k(x, y) = \frac{D_0^*(\mathrm{x}, \mathrm{y})}{D_0^k(\mathrm{x}, \mathrm{y})} \quad (9)$$

The technology gap ratio when considering the output-oriented technical efficiency measure is denoted as follows:

$$TGR_0^k\ (x,y) = \frac{TE_0^*(\mathrm{x,y})}{TE_0^k\ (\mathrm{x,y})} \tag{10}$$

$$\text{or: } TE_0^*(\mathrm{x,y}) = TE_0^k\ (\mathrm{x,y}) * TGR_0^k\ (x,y) \tag{11}$$

Figure 1 shows the relationship among three regional frontiers (1, 2 and 3 curves), the metafrontier (M curve) and the technology gap ratios.

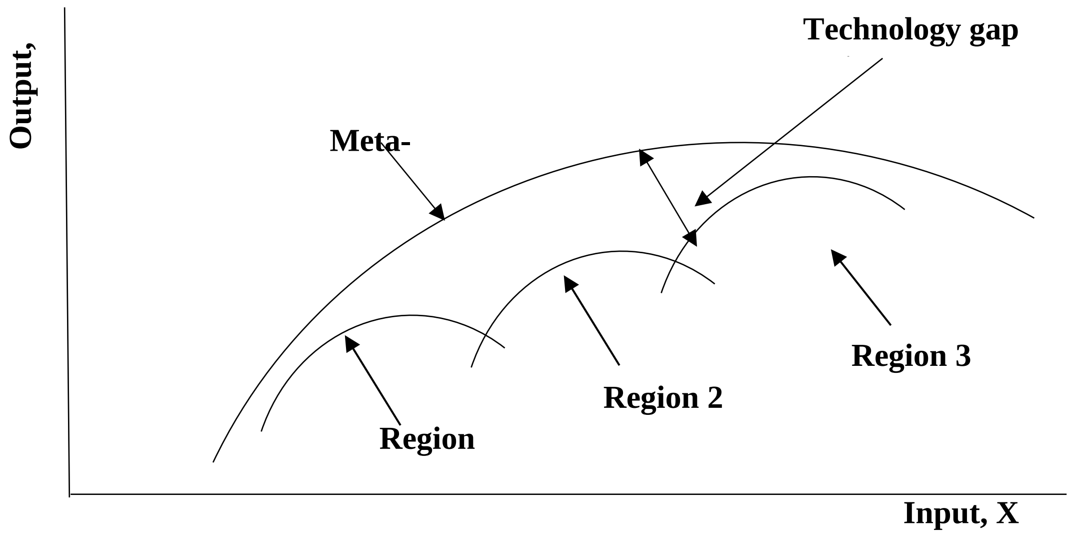

Figure 1 Technical efficiencies and Meta-technology ratios

In this study, the DEA approach will be used to measure the efficiency of rice farming in the four regions of Kenya and the meta-frontier approach will be used to analyse the technology gap ratios.

3.3: Regression analysis of determinants of efficiency

The standard methodology for investigating the technical efficiency determinants of a firm using DEA involves first generating the efficiency scores and evaluating the determinants in the second stage. In essence, the efficiency score become the dependent variable in the second stage and hence are regressed on covariates using the standard logit, probit models and truncated regressions. Studies that estimate determinants of efficiency by regressing efficiency scores on some covariates mostly specify a censored (tobit) model or a linear model based on ordinary least squares (see Aly et al., 1990; Chirikos & Sear 1994; Ray, 1991; Sexton et al., 1994; Cazals et al., 2002; Stanton, 2002; Daraio & Simar, 2005; Hoff, 2007; Banker & Natarajan 2008).

However, running a two-stage DEA is often criticised because the efficiency scores by nature are bounded at unity from above which makes it a limited dependent variable. Modelling of such bounded variables especially the non-binary ones with many observations at the extremes thus becomes a challenge since it makes the application of the standard linear models inappropriate**.** The logit and probit models provide a limited approach to solving the problem due to their strong distribution assumption for the underlying population. Tobit regressions become appropriate when the dependent variable is limited either above or below and when unbounded elsewhere. However, the two-limit tobit model does not observe efficiency scores of zero which implies that the estimates end up being based on the one limit tobit (Ramalho et al., 2010).

Recent developments in the two-stage process include the use of the bootstrapping technique which assumes that the accumulation of observations at unity is due to censoring (see Simar & Wilson, 2007). However, McDonald (2009) argues that efficiency scores being fractional data, may not be generated by a censoring process. McDonald (2009) adopts the ‘conventionalist’ approach in evaluating the two-stage process where the efficiency scores are measured relative to an estimated frontier, an approach that fails to solve the sampling variation issue. Banker & Natarajan (2008) that assumes a linear correlation exists between the logged technical efficiency scores and the covariates seemed favourable, however, the method only considers one parameter estimates and does not tackle the issue of hypothesis testing of the estimated variables.

The fractional regression model (FRM) developed by Papke and Wooldridge (1996) represents a viable solution to addressing the challenge of the second stage DEA analysis. The FRM is a class of functional forms extended from the general linear model. FRM has the following advantages: first, it helps to cater for the boundedness of the dependent variable from above and below. Second, it helps predict response values within the interval limits of the dependent variable and last, it also captures nonlinear data thus yielding better estimates. The only assumption required of FRM is a functional form of y so that the desired constraints on the dependent variable are imposed (Ramalho et al., 2010) as follows:

$$E(y|x) = G(X\theta) \tag{12}$$

where $G(.)$ denotes a nonlinear function that satisfies the condition $0 \leq G(.) \leq 1$. (13)

The model is estimated using four widely accepted models which include the logit, probit, loglog and complementary log referred to as Cloglog. The partial effects in all the models are denoted as:

$$\frac{\delta E\ (y|x)}{\delta x\mathrm{j}} = \theta_{jg}(x\theta) \tag{14}$$

In the recent works of Ramalho, et al. (2010) the authors recommend use of the fractional regression models to analyse efficiency determinants in the second stage. They consider a one and two-part models due to the differences in efficiency scores. The one part models assume that:

$$E(\hat{\theta}|w) = G(w\delta), \tag{15}$$

where G(.) denotes a probability distribution function. δ is unknown and is estimated by quasi-maximum likelihood (QML) that maximises:

$$\sum_{i=1}^{n}(\hat{\theta}_i \log(G(w_i\delta))) + (1-\theta_i)\log\left(1-G(w_i\delta)\right). \tag{16}$$

In the two-part models' the whole sample is used to estimate the model:

$$Prob\left(\hat{\theta}_i = 1 \middle| w_i\right) = F(w_i'\beta) \tag{17}$$

where β denotes an unknown parameter and F denotes a known probability distribution function. It is assumed that $\left(\hat{\theta}_i \middle| w_i\right) = G(w_i'\delta)$ for the responses in (0, 1) for the second part.

Following the recent works of E. A. Ramalho et al. (2010) the fractional regression models are used to evaluate farming process. The technical efficiency scores are regressed against the following determinants: age of the miller, experience of the miller, number of times the mill is serviced, number of years the mill has been in use and the type of energy used. A positive sign on the variables indicates that the variable positively affects efficiency and vice versa.

3.4: Study site and data

The target population consisted of adult (over 18 years) small-scale rice farmers located in Mwea and Western Kenya (Ahero, West Kano and Bunyala) rice schemes. The primary data used was from a household survey conducted in these rice regions. A sample of 835 small-scale rice farmers was drawn from the four rice schemes of Kenya. In Mwea, twenty-five rice farmers were randomly selected from twenty rice blocks (rice villages), making a sample total of 500 farmers. Mwea has about 6000 rice farmers thus making a sampling ratio of 8.3%. The rice schemes of western Kenya consist of Ahero, West Kano and Bunyala irrigation schemes. The Bunyala scheme has 133 farmers divided into seven blocks, hence a sample of thirty-five farmers was obtained making a sampling ratio of 26.3%. The West Kano scheme and Ahero schemes have twelve rice blocks each with a total of 819 and 1650 rice farmers respectively. A sample of 140 (17.1%) and 160 (9.7%) rice farmers was obtained from the West Kano and the Ahero schemes respectively.

The survey took place between April and June 2014. The data was collected using a questionnaire with pretesting done using a sample of 30 questionnaires. Data collection in each scheme was done using face to face interviews by enumerators. The data collected from the rice farmers' interviews and recorded in the questionnaires included output data (i.e. paddy amount harvested), input data included fertiliser amount, labour man days, seed quantity, pesticides quantity and land area (number of acres under rice). The data collected on socio-economic characteristics included farmers' age, farmer gender, household size, years of schooling, rice farming experience, distance to extension advice distance and market distance. Secondary supplemented the survey with further data on rainfall, humidity and temperature. After data coding, 62 observations (7.4%) were removed due to incomplete data thus making the total observations used for analysis to be 773.

3.1 Descriptive statistics of rice farmers' data

Table 1 provides summary statistics of the rice farmers' data. The statistics indicate that most farmers harvested an average of 4192kgs of paddy per year, with a maximum of 28500kg and a minimum of 225kg obtained. In terms of input quantities, land size ranged between 0.25 acres and 12 acres with an average of 1.98 acres. On average farmers used 222.4kg of fertiliser, with a maximum of 2400kg and a minimum of 24Kg. Farmers applied

0.76 litres of pesticides on average, with a maximum of 12 litres while a few farmers did not use pesticides. Given very few farmers did not apply pesticides, sample average estimates were used on the assumption that the effect the average had on the estimates was negligible. Farmers used 42.3kg of seed with a maximum and minimum of 330kg and 2kg respectively. Hired labour was on average 32.9 persons, with the maximum number being 178 while some farmers did not hire any workers. On average, farmers used 1.47 persons of family labour with a maximum of 23 persons per season. Thus, combining family and hired labour provided an average of 34.4 persons per season.

The demographic attributes of rice farmers captured included rice farmer's age, which ranged between 20 and 88 years, with an average of 48.6 years. A dummy variable captured the farmers' gender with males' being assigned one and females zero: 551 farmers were male and 222 females. On average, farmers had 8.1 years of schooling with the maximum number of years of schooling attained being 19 years while the minimum being a few farmers not having formal education. On average, farmers had 18.5 years of rice farming experience with a maximum of 80 years and no experience as a minimum. The market distance served as a proxy for infrastructure. Farms on average were located at 3.9km away from the market with the farthest being 20 km away. On average, farms were located 4.1km from extension advice with the farthest being 28km away and the nearest being locate a few metres away. The average rainfall ranged between 980.9mm and 1717.6mm with an average of 1113.0mm. Average humidity was 69.03% with a minimum of 64.5% and a high of 71.3%. The mean temperature was 22.7^0C, with a minimum of 22.3^0C and maximum of 23.3^0C. To cater for the regional differences, a dummy variable of one was assigned for farms located in the Mwea region and zero for those located in other regions. A dummy variable represented technology adoption, with one if a farmer adopted SRI technology and zero if otherwise. 605 (78.3%) of rice farmers were conventional farmers and 168 (21.7%) were SRI farmers. MaxDEA 6.0 software was used to generate the efficiency scores.

Table 1 Descriptive statistics of inputs and outputs for rice farmers

Variable	**Mean**	**Min**	**max**	**StdD**
Paddy (kg)	4192.00	225	28500	3139.59
Size of plot (acres)	1.98	0.25	12	1.31
Total fertilizer (kg)	222.39	24	2400	192.01
Pesticide applied (L)	0.76	0.01	12	0.92
Seed quantity (kg)	42.33	2	330	33.78
Labour hired (No)	32.97	0	178	20.43
Family labour used (No)	1.47	0	23	2.95
Total labour (No)	34.44	1	178	20.41
Unit prices				
Price per unit of paddy	46.07	25	100	10.56
Cost of land = Water cost per acre	2538.65	300	14800	1091.18
Average fertilizer per kg (Ksh)	53.57	0	138	13.33
Average cost of pesticides (per unit)	2.57	0.02	150	7.42
Cost of seed per Kg	88.17	20	200	16.30
Wage rate per head (Ksh)	1284.50	145.82	11610	1437.96
Inefficiency estimates				
Gender (1= male, 0 otherwise)		0	1	
Age (years)	48.63	20	88	13.54
Schooling (years)	8.07	0	19	3.83
Household members (No)	5.36	2	28	2.87
Experience (year)	18.46	1	80	13.52
Distance to extension advice (km)	4.09	0.007	28	3.85
Distance to the market place (km)	3.89	0.01	20	3.26
Average rainfall (mm)	1112.99	980.934	1717.6	189.55
Average humidity (%)	69.03	64.5	71.3	1.76
Average temperature (^{0}C)	22.65	22.3	23.3	0.47
Region dummy (1= Mwea, 0= Otherwise)		0	1	
Technology (1 = Adopted, 0 = Otherwise)		0	1	

Source: Field survey estimates and other sources

4.0 Results

4.1: Efficiency estimates and distribution

Table 2 provides the efficiency scores results. The overall mean technical and scale efficiency was 0.512 and 0.839 respectively, implying that there was a 48.8% greater potential to increase output further given the same input levels and 16.1% potential increase of output given optimal scale. 96.8% of the farms were found to be scale-inefficient, with 35.8% operating on increasing returns to scale, 60.9% operating under decreasing returns to scale and only 3.2% were scale efficient.

Table 2 Summary of technical, allocative and cost-efficiency

Range	Technical		Scale	
	No of DMUs	**%**	**No of DMUs**	**%**
<0.1	0	0	0	0
0.1-0.199	12	1.55	1	0.13
0.2-0.299	79	10.22	4	0.52
0.3-0.399	182	23.54	8	1.03
0.4-0.499	181	23.42	19	2.46
0.5-0.599	102	13.2	40	5.17
0.6-0.699	75	9.7	88	11.38
0.7-0.799	42	5.43	76	9.83
0.8-0.899	29	3.75	142	18.37
0.9-0.999	24	3.1	370	47.87
1	47	6.08	25	3.23
IRS	277	35.83		
DRS	471	60.93		
CRS	25	3.23		
Mean	0.512		0.839	
Minimum	0.109		0.197	
Maximum	1.000		1.000	
Std. Dev	0.214		0.158	

Source: Results estimates
Note: IRS = increasing returns to scale; DRS = decreasing returns to scale.

4.2 Meta-technology ratio

4.2.1 Hypothesis testing for technical and scale efficiency

To find if the technical, scale, allocative and cost-efficiency means were statistically different across regions, a Kruskal Wallis Test was carried out. The following hypotheses were tested:

Hypothesis 1: H_0 = mean technical efficiency is the same in all the regions

H_1 = mean technical efficiency is different across the regions

Hypothesis 2: H_0 = mean scale efficiency is the same in all the regions

H_1 = mean scale efficiency is different across the regions

The results indicate that the distribution of the means was statistically different across the regions since the null hypothesis was rejected in all cases (see Table 3). This implies that efficiencies varied across the regions which thus formed the basis for calculating the technology gap ratios between the regions as shown in Table 7.

Table 3 Hypothesis testing results for technical and scale efficiency

Variable	**P value**	**Result**
Technical efficiency	0.000	Rejected
Scale efficiency	0.000	Rejected

Source: Results estimates

4.2.2 Pooled and regional meta-frontiers of technical, allocative and cost-efficiency

Table 4 provides the meta-frontier estimates of the pooled data. The technical efficiency of Mwea, West Kano, Ahero and Bunyala was 0.556, 0.475, 0.402 and 0.45 respectively. Analysing regional efficiencies as shown in Table 5 indicates that the technical efficiency of Mwea, West Kano, Ahero and Bunyala was 0.557, 0.784, 0.833 and 0.937. Thus, the technology gap ratios as shown in Table 6 for Mwea, West Kano, Ahero and Bunyala was 0.998, 0.605, 0.482 and 0.480 respectively. The results thus suggest that a narrow gap existed between the region and the meta-frontier results for Mwea, while a wider gap existed for West Kano, Ahero and Bunyala. Mwea rice farmers were thus more technical efficient than rice farmers in the other schemes with Bunyala being worse off. Mwea may have an advantage over the other rice-growing regions due to its proximity to the capital city, Nairobi where key inputs such as fertiliser are easily accessible. The transportation cost of inputs e.g. fertiliser, seed and other inputs from Nairobi City make them more expensive and unaffordable in the other regions. As noted by Kherallah et al. (2002), fertiliser is much more expensive in Africa than elsewhere in the world due to high transportation costs, making it difficult for poor farmers to afford it. Mwea also benefits from its proximity to the Mwea Rice Research Centre and nearby higher institutions of learning conducting rice research in the area. Mwea also has large SRI experiment sites set up by researchers which encourage farmers to adopt such technology - all of which would impact on the efficient use of inputs. Further, the rice seed breeding centre is located in Mwea which makes the farmers easily access improved seed.

Table 5 Meta-frontier regional efficiencies estimates from pooled data

	Mwea		**West Kano**		**Ahero**		**Bunyala**	
Range	**No of DMUs**	**%**	**No of DMUs**	**%**	**No of DMUs**	**%**	**No of DMUs**	**%**
<0.1	0	0	0	0	0	0	0	0
0.1-0.199	1	0.21	3	2.36	7	5.34	1	3.13
0.2-0.299	26	5.38	19	14.96	30	22.90	4	12.50
0.3-0.399	101	20.91	32	25.20	39	29.77	10	31.25
0.4-0.499	117	24.22	30	23.62	29	22.14	5	15.63
0.5-0.599	66	13.66	18	14.17	11	8.40	7	21.88
0.6-0.699	59	12.22	7	5.51	6	4.58	3	9.38
0.7-0.799	31	6.42	6	4.72	5	3.82	0	0
0.8-0.899	23	4.76	2	1.57	3	2.29	1	3.13
0.9-0.999	19	3.93	5	3.94	0	0	0	0
1	40	8.28	5	3.94	1	0.76	1	3.13
Average	0.556		0.475		0.402		0.450	
Minimum	0.157		0.147		0.109		0.167	
Maximum	1.000		1.000		1.000		1.000	
Std. Dev	0.216		0.206		0.164		0.179	

Source: Results estimates

Table 6 Regional meta-frontier efficiencies estimate (when each region is analysed separately)

	Mwea Irrigation Scheme		West Kano Irrigation scheme		Ahero Irrigation Scheme Allocative		Bunyala Irrigation Scheme Cost	
Range	**No of DMUs**	**%**	**No of DMUs**	**%**	**No of DMUs**	**%**	**No of DMUs**	**%**
<0.1	0	0	0	0	0	0	0	0
0.1-0.199	1	0.21	0	0	0	0	0	0
0.2-0.299	25	5.18	0	0	4	3.05	0	0
0.3-0.399	100	20.7	2	1.57	2	1.53	0	0
0.4-0.499	118	24.43	7	5.51	4	3.05	2	6.25
0.5-0.599	65	13.46	10	7.87	17	12.98	0	0
0.6-0.699	60	12.42	24	18.90	8	6.11	0	0
0.7-0.799	32	6.63	26	20.47	7	5.34	2	6.25
0.8-0.899	22	4.55	14	11.02	12	9.16	3	9.38
0.9-0.999	19	3.93	7	5.51	24	18.32	0	0
1	41	8.49	37	29.13	53	40.46	25	78.13
Average	0.557		0.784		0.641		0.501	
Minimum	0.157		0.350		0.341		0.220	
Maximum	1.000		1.000		1.000		1.000	
Std. Dev	0.216		0.183		0.131		0.161	

Source: Results estimates

Table 7 Summary of the technical efficiency means and the gap ratios

		Mwea Irrigation Scheme	West Kano Irrigation Scheme	Ahero Irrigation Scheme	Bunyala Irrigation Scheme
Pooled frontier	Average	0.556	0.475	0.402	0.450
	Minimum	0.157	0.147	0.109	0.167
	Maximum	1.000	1.000	1.000	1.000
	Std Dev	0.216	0.206	0.164	0.179
Region frontier	Average	0.557	0.784	0.833	0.937
	Minimum	0.157	0.350	0.250	0.456
	Maximum	1.000	1.000	1.000	1.000
	Std Dev	0.216	0.183	0.215	0.141
	Gap Ratio	**0.998**	**0.605**	**0.482**	**0.480**

Source: Results estimates

4.3 Determinants of efficiency

Table 8 provides the FRM estimates for technical efficiency. In the one-part models (linear models) age, farmer's gender and adopting technologies were significant at the 10% and 5% levels, thereby explaining why some farmers were efficient. However, experience, extension, market distance, years of schooling, humidity, rainfall and temperature did not explain the inefficiency, since the variables were not statistically significant. At 10% and 5% significance levels for the logit and cloglog model, age, farmer's gender, humidity, rainfall, temperature and adopting technologies explained the inefficiency.

An examination of the second part of the two-part models, showed that adopting technologies was the reason why some farmers were more efficient (5% significance level for the cloglog and at 10% significance level for the logit model). In examining why some farmers were inefficient, their age, gender and level of humidity reduced their efficiency scores at 5% and 1% significance level for all the models. Adopting technologies and temperature reduced their inefficiency at the 5% and 10% significance level for all the models.

The role of gender in rice farming remains important. The results indicate that a rice farmer's gender had a negative relationship with efficiency, implying that males were more inefficient in rice farming than the females. The finding contradicts the bulk of the existing literature which finds males more efficient than females (Ironkwe et al., 2014; Oladeebo, 2012). However, it may be assumed that given women play a critical role in rice farming by providing close to half of the total labour input in rice farming, then this finding holds.

The age of the farmer was found to be negatively correlated with efficiency. The finding corroborates the works of Mugera and Featherstone (2008) who found that age increased inefficiency among a sample of 126 people rearing hog in the Philippines. The results also confirmed that young farmers tend to adopt newer technologies faster than the older farmers hence, the higher efficiency.

The role of climatic factors in rice farming remains important. The average humidity and rainfall, affected efficiency negatively, while temperature positively affected efficiency. Sarker et al. (2012) and HoAfricain et al. (2013) also found rainfall to be negatively associated with AUS variety rice farming in Bangladesh. However, in relation to humidity and temperature, this study results contradict the findings of these authors. However, Banaszek and Siebenmorgen (1990) found that lower relative humidity reduced head rice yield less while Mahmood et al. (2012) found that in India's Punjab province an increase in temperature by 1.5^0C and 3^0C increased rice yield by 2.09% and 4.33%, respectively. Rice requires optimum rainfall, temperature and humidity for its vegetative growth and to produce paddy therefore policies that spearhead adaptive strategies to mitigate adverse effects of the climatic factors would benefit rice farmers.

Adopting technologies has been found the key to increasing rice output particularly in Asia. In this study, those farmers who adopted improved seed and water saving technologies were more efficient than the conventional farmers. Thus, investing in improved rice technologies will clearly help increase rice output in Kenya.

Table 8 Determinants of technical efficiency

	One-part models				Two-part models						
					1st Part		2nd Part				
Variable	**Linear**	**Tobit**	**logit**	**cloglog**	**logit**	**cloglog**	**Linear**	**logit**	**probit**	**loglog**	**cloglog**
Intercept	2.140*** (0.345)	2.211*** (0.364)	6.677 *** (1.153)	4.450*** (0.846)	21.97 (1037)	21.44 (991.2)	1.761*** (0.297)	5.144*** (1.012)	3.210*** (0.632)	3.935*** (0.699)	3.469*** (0.759)
Age (years)	-0.002* (0.001)	-0.002* (0.001)	-0.006* (0.003)	-0.005** (0.002)	-0.010 (0.018)	-0.010 (0.017)	-0.002** (0.001)	-0.006** (0.003)	-0.004** (0.002)	-0.004** (0.002)	-0.005** (0.002)
Experience (years)	0.000 (0.001)	0.000 (0.001)	0.001 (0.003)	0.000 (0.002)	0.003 (0.017)	0.003 (0.016)	0.000 (0.001)	0.001 (0.003)	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)
Extension (km)	-0.001 (0.002)	-0.001 (0.002)	-0.003 (0.009)	-0.002 (0.006)	-0.012 (0.046)	-0.011 (0.044)	-0.000 (0.002)	-0.002 (0.007)	-0.001 (0.005)	-0.001 (0.005)	-0.001 (0.005)
Gender (0 = female; 1=male)	-0.039** (0.017)	-0.041** (0.018)	-0.160** (0.071)	-0.112** (0.049)	-0.232 (0.332)	-0.224 (0.317)	-0.034** (0.015)	-0.138** (0.062)	-0.087** (0.039)	-0.098** (0.044)	-0.101** (0.044)
Humidity (%)	-0.024 (0.048)	-0.024 (0.050)	-0.114*** (0.035)	-0.097*** (0.025)	-2.355 (333.7)	-2.335 (319.0)	-0.023 (0.040)	-0.111*** (0.029)	-0.067*** (0.018)	-0.063*** (0.020)	-0.094*** (0.022)
Market (km)	-0.001 (0.003)	-0.001 (0.003)	-0.002 (0.012)	-0.001 (0.008)	0.000 (0.053)	0.001 (0.051)	-0.000 (0.002)	-0.002 (0.009)	-0.001 (0.006)	-0.002 (0.007)	-0.001 (0.007)
Rainfall (mm)	-0.000 (0.000)	-0.000 (0.001)	-0.001*** (0.000)	-0.001*** (0.000)	-0.024 (3.366)	-0.024 (3.218)	-0.000 (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
School (years)	-0.001 (0.002)	-0.001 (0.002)	-0.005 (0.009)	-0.004 (0.007)	0.011 (0.048)	0.011 (0.046)	-0.002 (0.002)	-0.007 (0.008)	-0.004 (0.005)	-0.005 (0.006)	-0.005 (0.006)
Technologies (1=adopted; 0= not adopted)	0.048** (0.018)	0.052** (0.019)	0.197** (0.079)	0.146*** (0.056)	0.735* (0.347)	0.705** (0.328)	0.030* (0.016)	0.121* (0.068)	0.075* (0.042)	0.082* (0.048)	0.091* (0.050)
Temperature (^{0}C)	0.022 (0.166)	0.018 (0.174)	0.142 (0.117)	0.155* (0.085)	7.442 (1162)	7.392 (1111)	0.034 (0.140)	0.192* (0.101)	0.112* (0.063)	0.085 (0.070)	0.185** (0.075)
Sigma		0.215*** (0.006)									
Number of observations	773	773	773	773	773	773	726	726	726	726	726
R-squared	0.093	1.967	0.093	0.094	0.024	0.025	0.082	0.082	0.082	0.082	0.083

Source: Results estimate

4.4 Conclusion and recommendations

The technical efficiency of a sample of 773 rice farmers from four rice-growing schemes in Kenya were measured using DEA and the efficiency determinants were quantified using FRM. The results indicate a significant variation of the efficiency scores among the four regions.

The overall mean technical and scale efficiency was 0.512 and 0.839 respectively, implying that there was a 48.8% greater potential to increase output further given the same input levels and 16.1% potential increase of output given optimal scale. 96.8% of the farms were found to be scale-inefficient, with 35.8% operating on increasing returns to scale, 60.9% operating under decreasing returns to scale and only 3.2% were scale efficient.

The average technical efficiency of Mwea, West Kano, Ahero and Bunyala was 0.556, 0.475, 0.402 and 0.45 respectively which implies that on average output would be increased by 44.8%, 52.5%, 59.8% and 55% in Mwea, West Kano, Ahero and Bunyala respectively given the same level of inputs. Mwea efficiency results were close to the meta-frontier results of the pooled data thus indicating a very narrow gap between the two estimates. The West Kano, Ahero and Bunyala efficiency scores were higher than that of the meta-frontier thus indicating a gap between the regional and meta-frontier results. Thus, Mwea appeared to be closer to the frontier, while Bunyala was very far from the frontier. The factors found to be associated with technical efficiency included: gender, age, humidity, rainfall, temperature and adopting technologies.

Based on these findings, some important policy implications can be drawn. Policy interventions should aim at improving overall technical, cost and allocative efficiency of rice farming in Kenya. Thus, policy-makers should focus on enhancing rice farmers' technology adoption and training to bridge the inefficiency gap. Putting in place a planting schedule programme that will allow rice farmers to utilise the land during the fallow months for short duration crops such as tomatoes, watermelons and beans would be one important means of helping farmers to enhance their livelihoods. Policies that target the challenges young farmers and either gender face in the rice farming systems will also contribute to narrowing the efficiency gap between the older and younger farmers, and between the male and female rice farmers. Policies that would narrow the technological gap between Mwea and the Western schemes would also be beneficial to the farmers. Spearheading adaptive strategies to mitigate adverse effects of climatic factors especially temperature, rainfall and humidity would be equally beneficial for farmers. In addition, very inefficient rice farmers should be encouraged to exit the industry to enable Policy-makers to reallocate the resources (especially land and water) to other more economic activities.

5.0 References

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