Stochastic Meta Frontier Analysis of Smallholder Rice Farmers' Technical Efficiency

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Abstract

The aim of this study is to compare the technical efficiency of System of Rice Intensification (SRI) and Conventional Rice Production System (CRPS) farmers in Mali. Using cross-sectional data for 208 randomly selected rice farmers, the Stochastic Meta Frontier model is applied. The results indicate that the mean technical efficiency is 0.96 and 0.79 for SRI and CRPS respectively. This implies that SRI farmers were more technically efficiency than their counterpart. Similarly, the mean technology gap ratio was 0.98 and 0.91 for SRI and CRPS farmers, respectively. We also find that rice paddy production (SRI) was positively influenced by labor and negatively by organic manure while rice paddy production (CRPS) was positively linked with inorganic fertilizer and land. Further investigation reveals that family labor and flooding level increased the technical inefficiency for SRI adopters whereas education had a negative impact. For the CRSP farmers, the current factors were unable to account for technical inefficiency except age of farm household head. Our study finds strong cause to encourage SRI adoption as it could be the highly searched for solution for farmers to increase their yields and eventually enhance their food security status.

Keywords: stochastic meta-frontier model, technical efficiency, technology gap ratio, the system of rice intensification, Conventional Rice Production System, Mali

1. Introduction

Cereals are the staple food in Mali. Particularly, rice remains the most consumed representing about 30% of total cereal consumption (Coulibaly, Savadogo, & Diakité, 2017). The local consumption per capita has increased from 69.7 kg/person/year in 2010 to 105 kg/person/year in 2013 (Van Oort et al., 2015). Rice production is also continuously increasing at a rate of 4% and contributes about 5% to Gross Domestic Product GDP which is 8.3% of the agricultural flow (Coulibaly et al., 2017). Consequently, the Malian government considers rice as one of the strategic crops in the achievement of food security. At present, the national food security programs rely on the production and the availability of rice (Balie, Aparisi, Gourichon, Diakite, & Diallo, 2013). However, there is currently a huge deficit between local production and consumption leading to increased rice importation (Gajigo, Denning, & Dawe, 2010). The rapid population growth, dietary diversification, rising income and urbanization are some of the reasons for the increasing rice consumption (Coulibaly et al., 2017).

After the global food crisis in 2007, the government of Mali launched the "Initiative Rice" program in 2008 which was followed by the National Rice Development Strategies (NRDS) in 2009 (Balie et al., 2013). These innovative programs were initiated to enhance intensification of rice production, improve self-sufficiency, and, increase the productivity of rice farmers through providing subsidies on seed, fertilizer and facilitate access to credit for rice producers (Roy, 2010). Most of these programs were implemented using the CRPS approach which is a widespread rice farming practice characterized by continuous flooding and massive agrochemical use (He, 2010). Rice is mainly cultivated in lowland ecosystem which is flooded during the whole cropping cycle. The

flooded land helps weed control, land leveling, and transplanting. However, the practice may destroy the soil structure under saturated soil moisture conditions and lack of sustainability in rice farming. In addition to decreasing land fertility, erratic rainfall, inappropriate management of production resources, rice production cannot meet the increasing demand to provide self-sufficiency in Malian.

These factors inspired a technological dimension in rice farming using the System of Rice Intensification (SRI) principles. The SRI program started in 2007 in Timbuktu, northern region of Mali (Styger et al., 2011). The fundaments of the SRI techniques are low external inputs use, focused on organic matter use rather than chemical fertilizer, and intermittent irrigation during the vegetative stage (Uphoff & Dazzo, 2016). This aims to produce rice in a healthy and environmentally sustainable manner.

According to Xu and Jeffrey (1998), introducing new agricultural technologies do not result consequently in improving productivity in most developing countries. Therefore, an efficiency analysis was chosen as a way of investigating the reason that prevents productivity and efficiency growth in Malian rice farming.After its establishment by Farrell (1957), technical efficiency and technological gaps have been widely used in various agricultural researches to estimate the performances of given firms (Anyanwu, 2011; Dhungana, Nuthall, & Nartea, 2004; Mailena, Shamsudin, Radam, & Mohamed, 2014; J. A. Onumah, E. E. Onumah, Al-Hassan, & Bruemmer, 2013; Toma, Dobre, Dona, & Cofas, 2015). Likewise, in Mali recent studies include, Audibert (1997) measured technical inefficiency effects of paddy farmers in "*office du Nige ON*" in Mali, and Coulibaly et al. (2017) applied stochastic production frontier in measuring rice technical efficiency in ON (Audibert, 1997; Coulibaly et al., 2017; Diamoutene, Diakite, & Coulibalily, 2018). However, no study has attempted to compare the relative technical efficiency levels between the SRI and CRPS farms in Mali. Most studies applied the stochastic frontier analysis (SFA) an estimation procedure that does not offer merits when it comes to comparing groups of firms under different technology. The meta-frontier analysis (MFA) is more suitable for such comparative analysis with a group of firms using different technology (Battese, Rao, & O'Donnell, 2004; Huang, Huang, & Liu, 2014; O'Donnell, Rao, & Battese, 2008).

Mali is one of the granaries of rice production in West Africa. It is ranked second behind Nigeria, with paddy production of about 2.7million tons in 2017 (Styger & Traoré, 2018). Currently, it covers about 91% of the self-sufficient and the remaining gap is covered through imports from Asia. The average imported quantity is about 200.000 tons/year and an annual spending of 24 billion FCFA (DNCC, 2014). However, rice productivity is still low (about 3.6 t/ha) (ORYZA, 2014). The low productivity aggravates the imbalance between the demand and supply of rice in the market and therefore the production remains unsubstantial to satisfy the consumption needs of the growing population.

Therefore, this study aims to comparatively analyze the technical efficiency level of SRI and CRPS rice production system in Mali. In order to achieve this broad objective, the study (1) analyzes the productivity level of SRI and CRPS, (2) estimates the level of technical efficiency and the technology gap between these two production systems, and (3) identifies the determinants of technical inefficiency.

The study contributes to the literature in two ways. First, we use a method that is consistent with rice production reality in Mali to estimate the technical efficiency of farmers. Meta frontier analysis allows for the estimation of group specific frontier which is useful for policy makers. Finally, we compare two production practices widely used by rice farmers in an attempt to facilitate improvement in productivity and environment protection. This is very beneficial for developing countries if they are to meet the rising food demands.

The remaining part of this paper is structured as follows: Section 2 describes the materials and methods; Section 3 presents the results and discussion; Section 4 closes with conclusion and policy recommendation.

2. Material and Methods

2.1 Data

The study was conducted in San west plain commonly named ARPASO plain and it is the main zone where SRI practices are well developed (see Figure 1). It has a total geographic area of 7262 km^2 and a population of 334911 habitats (Census, 2009). The district of San is characterized by a semi-arid climate and irrigated by the tributaries of Bani River. The average annual precipitation varies between 400-700 mm and the average temperature is between 16-39 °C. The agricultural lands are 90% constituted of loamy, and sandy soil. Specifically, rice is cultivated on 75% of agricultural lands and both SRI and CRPS are practiced by producers. Currently, the cultivated areas represent about 52% of its potential (2335.35 ha) of which 1309 ha is under total water control whereas 1026.35 ha is under control submersion. ARPASO is an irrigated land managed by a farmers' association called the Rice Farmers' Association of San West Plain created in 1976. The association is

commonly known as ARPASO which is a French acronym of "*Association des Riziculteurs de la Plaine Aménagée de San Ouest*". At present the association accounts for 5090 members including 327 females' households (ARPASO, 2018).

Four zones chosen for the study includes Bô-were village, Demba-were village, Tiekelenso village and the town of San (see Figure 1). A list of the registered farmer was obtained from ARPASO and the regional sector of agriculture. These offices provided an updated list of farmers with plots references which were used to do the sample selection of 104 CRPS farms. The identification of selected farmers was done with the help of the chief of the section.

A random sampling technique based on farmers' list was used to select farms which were either growing rice under SRI or CRPS. 104 SRI farmers have been randomly selected form the projects implemented during the 2017-2018 farming season. Due to the constraint of some farmers' desertion from SRI practice, and lack of updated registered SRI farmers list in the record, it was difficult to know the current total farmers' numbers of SRI. However, they were able to provide a list of three programs which implemented SRI in the 2017-2018 cropping season with FAO, APEJ, FARM.

A well-designed questionnaire was used to collect information on farms' output, input, price data, and exogenous variables. These farms could be single or double cropping for the study campaign. But the analysis accounts only for the information related to the main farming season. A total sample size of 208 is drawn for the study which includes 104 SRI farms and 104 CRPS farms.

In an attempt to collect quality data, prior to the period of data collection, a pilot survey was done in San. This permitted correction of the questionnaire in the light of errors and omission detected.
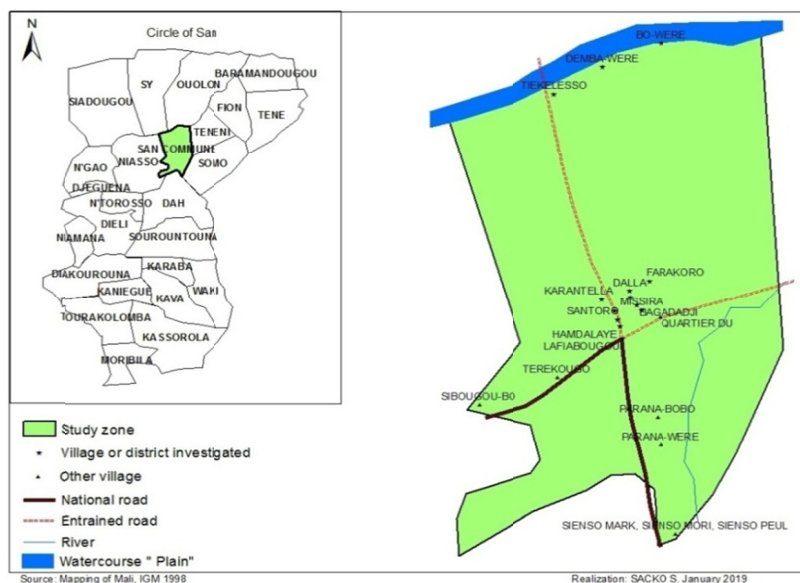

Figure 1. Representation of the study area

Source: Mapping of Mali, IGM 1998, Adapted by Sacko (2019).

2.2 Empirical Strategy

Following Huang et al. (2014), this research considers the stochastic meta frontier function to estimate the optimal potential output for the rice industry in Mali. The meta frontier is used to investigate the technical efficiencies for dissimar technologies like this case. It is a smooth function that envelopes the two frontiers of the individual rice farming system as shown in the following Figure 2. The main difference between stochastic meta frontier proposed by Huang et al. (2014) and the classical meta frontier developed by Battese et al. (2004) lies in the second step. In the Huang et al. (2014) approach, a stochastic frontier approach is used in the second step to estimate the metafrontier while the programming techniques are used with the method developed by Battese et al. (2004). Huang et al. (2014) approach provides desirable statistical properties for the estimators and allows the statistical inferences to be drawn.

Unlike other approaches of technical efficiency estimations, the stochastic meta-frontier seeks to estimate the production frontier of each group under the assumption that they have a different frontier. This is more effective in comparing technical efficiency of two groups.
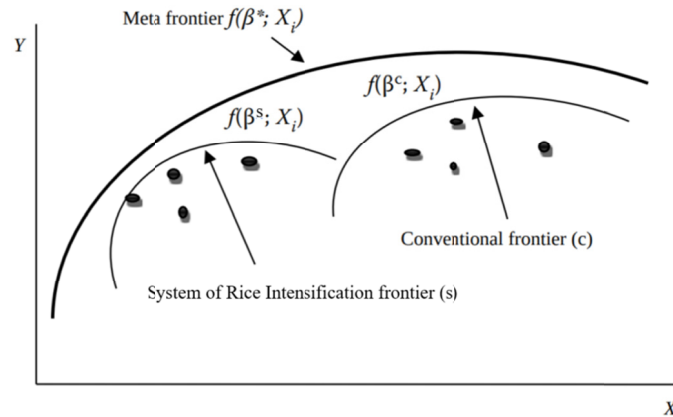

Figure 2. Meta frontier model

Source: Adapted from (Battese et al., 2004).

Assuming that the rice industry has j production groups, the stochastic function of the farm or decision-making unit (DMU) i is defined as follows as:

$$Y_{ji} = f^j(X_{ji})e^{V_{ji}-U_{ji}}, j = 1, 2, \ldots J; i = 1, 2, \ldots N_j \tag{1}$$

Where, Y_{ji} denotes the scalar output for the ith firm for the jth and X_{ji} input vector of the ith farm inputs used in the jth group. V_{ji} represents the random errors statistical noise, whereas U_{ji} the non-negative random errors represent the inefficiency error. V_{ji} is supposed to be distributed independently and identically as, N (0, σ_v^{j2}). V_{ji} is also suppose to be independent of U_{ji}. U_{ji} is truncated and normally distributed with u_i^j as mean and σ_u^{j2} as variance $N^+[U^j(Z_{ji}), \sigma_u^{j2}(Z_{ji})]$, and Z_{ji} is a vector of exogenous variables.

Technical efficiency (TE) represents the difference between the observed output and the highest possible output that farmers can get with the available set of inputs. For the ith farm, the technical efficiency TE_i is defined as the ratio of the obtained output to the equivalent potential output. (TE) in production is then expressed as:

$$TE_i^j = \frac{Y_{ji}}{f^j(x_{ji})e^{V_{ji}}} = e^{-U_{ji}} \tag{2}$$

The variation across the individual group-specific production technology is expressed by the superscripted j in the production frontier function $f^j(.)$. Specifically, $f^j(X_{ji}) = e^{X_{ji}\beta^j}$, where, β^j denotes the parameters associated with the x-variables for group-j frontier. The technical efficiency can be associated with a set of within-group firm-specific exogenous variables Z_{ji}.

The meta-frontier production function for the two production systems is defined as $f^M(X_{ji})$, where, the function is the same for SRI and CRPS. The following relationship shows that the frontiers of the all individual groups $f^j(X_{ji})$ are enveloped by the meta-frontier by definition $f^M(X_{ji})$.

$$f^j(X_{ji}) = f^M(X_{ji})e^{-U_{ji}^M}, \forall j, i \tag{3}$$

Where, $U_{ji}^M \geq 0$. Thus, $f^M(X_{ji}) \geq f^j(X_{ji})$ and the technology gap ratio (TGR) which is the ratio of the jth group's production frontier to the meta frontier and expressed as:

$$TGR_i^j = \frac{f^j(X_{ji})}{f^M(X_{ji})} = e^{-U_{ji}^M} \leq 1 \tag{4}$$

The TGR_i^j represents the gap between the given rice production technology and the technology available. The higher the ratio, the closer the gap. It is also defined as the choice of a particular technology that depends on both economic and non-economic production environments. The TGR depends on the accessibility and extent of adoption of the available meta-frontier production technology illustrated by meta-frontier production model in Figure 2.

At a given input level X_{ji}, a firm's observed output Y_{ji} relative to the metafrontier $f^M(X_{ji})$ consists of three components: the TGR, the firm's TE and the random noise component, expressed as follow:

$$\frac{Y_{ji}}{f^M(X_{ji})} = TGR_i^j \times TE_i^j \times e^{V_{ji}} \tag{5}$$

It should not be noted that, although both the technology gap ratio $TGR_i^j \leq 1$ and the firm's technical efficiency $TE_i^j \leq 1$ are bounded, the metafrontier $f^M(X_{ji})$ does not necessary envelop all firms' observed outputs Y_{ji}. The TGR_i^j is significant in explaining the ability of the individual farms in the SRI group to compete with other farms in the CRPS group. It corrects the technical efficiency score of the farmers that apply different technology and makes them comparable using the distance between the technology (SRI and CRPS) frontier and the leading frontier. By accounting for the random noise component, the decomposition in (5) can be expressed alternatively as:

$$TE_{ji}^* = \frac{Y_{ji}}{f^M(X_{ji})e^{V_{ji}}} = TGR_i^j \times TE_i^j \tag{6}$$

Where, TE_{ji}^* expresses the firm's technical efficiency with respect to the meta-frontier production technology $f^M(X_{ji})$ as opposed to the firm's technical efficiency TE_i^j with respect to the group-j production technology $f^j(X_{ji})$.

2.3 Model Specification

The model proposed by Huang et al, (2014) consists of two steps, the first step is to estimate the group-specific stochastic frontier. The second stage estimates the stochastic meta-frontier by pooling the data. This stage uses the estimate of the group-specific output. Before the aforementioned estimation, the study investigated some hypotheses to choose the appropriate production function for the database. The investigation indicates the Cobb Douglas CD model was rejected in favor of the translog for SRI and pooled data except for the CRPS where CD is suitable. Then the two models are specified as (7) for translog function and (8) for CD.

$$\ln Y_i = \ln \beta_0 + \sum_{j=1}^6 \beta_j \ln X_{ji} + \frac{1}{2} \sum_{j=1}^6 \sum_{k=1}^6 \beta_{jk} \ln X_{ji} \ln X_{ki} + (v_i - u_i) \tag{7}$$

$$\ln Y_i = \ln \beta_0 + \sum_{j=1}^6 \beta_j \ln X_{ji} + (v_i - u_i) \tag{8}$$

where, Y_i = the level of output (kilograms), X_1 = labour (cfa), X_2 = organic manure (kg), X_3 = seed (cfa), X_4 = inorganic fertilizer (cfa), X_5 = land (hectares), X_6 = Other inputs (cfa) which and include water cost, herbicide cost, and, insecticide cost. The deviation of obtained output to its maximum potential depends on the non-negative random errors u_i, representing the technical inefficiency. If $u_i = 0$, then the observed output will be situated to its potential, if $u_i > 0$, then the observed output will be located below its maximum potential.

Thus, the meta-frontier model is expressed as:

$$\ln Y_{hat} = \ln \beta_0^* + \sum_{j=1}^6 \beta_i^* \ln X_{ji} + \frac{1}{2} \sum_{j=1}^6 \sum_{k=1}^6 \beta_{jk}^* \ln X_{ji} \ln X_{ki} + (v_i^* - u_i^*) \tag{9}$$

The method to explain inefficiency can as well be specified as:

$$\mu_i = \delta_0 + \sum_{m=1}^7 \delta_m Z_{mi} \tag{10}$$

Where, Z_{mi} is a vector of factors influencing technical efficiency such that Z_1 = gender, Z_2 = age of farm decision maker; Z_3 = family member, measured as the number of the person in the farmer house actif in farm work; Z_4 = educational level of farmer; Z_5 = experience in rice farming, measured as number of year; Z_6 = participation to training program; Z_7 = flooding level or water depth in the farm after irrigation, measured in centimeter cm.

In this study, the Tobit model was employed to evaluate the factors influencing technical efficiency. Due to its censoring attributes, estimations from the Tobit are more consistent than from OLS. The specification of the Tobit is as follows:

$$u_i^* = \delta_0 + \sum_{m=1}^7 \delta_m Z_{m_i} + \varepsilon_i, \ \varepsilon_i \sim N(0, \sigma^2) \tag{11}$$

$$u_i = \begin{cases} u_i^* & \text{if } u_i^* > 0 \\ 0 & \text{if } u_i^* \leq 0 \end{cases} \tag{12}$$

Where, u_i^* is a latent (*i.e.*, unobservable) variable. This variable linearly depends on Z_{mi} via a parameter (vector) δ_m which determines the relationship between the independent variable Z_{mi} and the latent variable.

3. Results and Discussion

3.1 Summary Statistics

Summary statistics of the socio-economics variables for the study sample are summarized in Table 1. The results exhibit that the average paddy production of the SRI sample was 6697 kg/ha (6.7 t/ha). The minimum production was 4750 kg/ha (4.7 t/ha) and the maximum was 9000 kg/ha (9 t/ha). The Standard Deviation (SD) of the production was quite high (845.508) which showed the large variability on paddy production among the SRI sampled farms. Among the main inputs, the labor cost (67870 Cfa) had the highest mean followed by other inputs cost (30625 Cfa) which included water, herbicides and insecticides, inorganic fertilizers cost (26937 Cfa), and seed cost (4313 Cfa) respectively. The mean of land was 0.47 ha with a maximum of 2 ha per farm. The SD of land was quite low (0.21) showing the variability of land size among the sampled farms was not larger. The organic manure was measured in kilogram because they were too many different ways of getting this input. Some farms bought it and others made by their self or from agreements between farmers and livestock keepers. On average, the organic manure used on paddy farms was 2690.385 kg/ha (2.7 t/ha). The minimum and maximum quantities were 250 kg/ha (0.25 t/ha) and 20000 kg/ha (20 t/ha) respectively. Yet, the variability of using organic manure among the sampled farms was quite large since the SD for organic fertilizer was 3525.332.

Moreover, in term of socio-economic characteristics, SRI sample had fair access to extension services: 98% had received training on rice production best practices and 100% had access to credit. Among the sampled farms, male owner was the highest about 86% against female which was only14%. The total control water system was the dominant about 98% and most farms were cultivated by its owner about 97%. The soaking of rice seed before nursery allows the quick germination and reduces the nursery time. The young seedling could then be planted starting from 12 days. Yet only 22% of the SRI sample did this practice among others.

In contrast, CRPS farms had an average production of 5610.905 kg/ha (5.6 t/ha). The variability among the farms was very large as the SD for production was 1581.043. The minimum and maximum paddy production were 545.4545 kg (0.5 t/ha) and 9461.539 kg/ha (9.5 t/ha) respective. Among the main inputs, the labor cost was also the highest (54782 Cfa), followed by the inorganic fertilizer cost (52500 Cfa), the other inputs cost (30631 Cfa), and, the seed cost (15649 Cfa). The mean of land was 0.46 ha with a maximum of 1.5 ha per farm. The SD of land was quite low (0.29) showing the variability of land size among the sampled farms was not larger. On average, the organic manure used on paddy farms was 4715.865 kg/ha (4.7 t/ha). The minimum and maximum quantities were 0 kg/ha (0 t/ha) and 75 000 kg/ha (75 t/ha) respectively. Yet, the variability of using organic manure among the CRPS sampled farms was quite large since the SD for organic fertilizer was 8077.135.

Furthermore, the socio-economic characteristics of CRPS sampled farms showed that more than half of the farm owners (69%) did not receive any training on best production practices. The female owner was 11% against males that were 89%. The access to credit was quite high about 93%. Also, the overall CRPS farms were cultivated by their owner 100%. The fast germination practice was used by only 10%.

The pooled sample exhibits that on average paddy production was 6153.964 kg/ha (6.1 t/ha). The minimum and maximum were 545.454 kg/ha (0.5 t/ha) and 9461.539 kg/ha (9.4 t/ha). The SD was high about 1376.903. The highest input cost mean was labor (61326 Cfa), followed by inorganic fertilizer (32739 Cfa), other input (30627 Cfa), and seed (9981 Cfa). The Land had the lowest mean about 0.468 ha and its variability among the pooled sampled was not large since SD for land was 0.22.

The pooled sample showed that more than half farm owners had informal education. About 45% had elementary Arabic school level and 9% had the advanced Arabic school level. The remaining 46% of farm owners attained formal education. The highest percentage was held by technical and professional level about 20%, followed by 11% for primary school, 6% for junior high school, 3% had university level, and, 1% had a senior high secondary school. Male held the majority of the farm about 87%. The soil fertility in the study area is quite good among the sampled farms (56%) with a medium slope (67%) and the type loamy (59%). Also, the pooled sample had fair access to extension services, 63% and 96% have accessed training on best rice farming and credit support on fertilizer and water with ARPASO. The predominant irrigation system among the farms' was the total control of water (80%) and partial control (20%). The farms were sometimes constrained to exogenous factors like disease and pest attack. About 21% of the sampled farms were attacked whether by disease or pest during the 2017-2018 season campaign. The frequency for a farm to escape attacks was about 77%.

Table 1. Summary statistic of main variables

Variable Category	SRI (N=104)			CRPS (N=104)			Pooled (N=208)		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Factors of production									
Production (kg)	6697.023 (845.508)	4750	9000	5610.905 (1581.043)	545.4545	9461.539	6153.964 (1376.903)	545.4545	9461.539
Seed cost (cfa)	4313 (3528)	700	18750	15649 (10607)	25	52500	9981 (9719)	25	52500
Infer cost (cfa)	26937.500 (13080.77)	6250	105000	52500 (18170.28)	18750	100000	32739.18 (16829.86)	6250	105000
Organic fertilizer (kg)	2690.385 (3525.332)	250	20000	4715.865 (8077.135)	0	75000	3703.125 (6298.971)	0	75000
Total labor cost (cfa)	67870.19 (15036.32)	33750	108000	54782.2 (20968.92)	21250	109500	61326.2 (19347.24)	21250	109500
Other input cost (cfa)	30624.76 (14544.04)	15000	140000	30631.15 (17277.01)	11500	101150	30627.96 (15930.48)	11500	140000
Land (ha)	0.468 (0.216)	0.250	2	0.458 (0.290)	0.170	1.490	0.463 (0.255)	0.170	2
Explanatory variable									
Gender: (1 if men)	86.54			89.42			87.98		
Training: (1 if accessed)	98.08			28.85			63.46		
Credit/Support: (1 if accessed)	100.00			93.27			96.63		
Land status: (1 if owner)	97.12			100.00			98.08		
Soaking: (1 if seed soaked 24 hours before nursery)	22.12			9.62			15.87		
Water control system: (1 if full control	98.08			61.54			79.81		

Notes. Figures in parenthesis are standard deviations and the values under explanatory variables are percentages.

Source: Authors' estimation.

3.2 Hypotheses Test for the Analysis

Table 2 includes the results of the hypotheses tested. The first hypothesis tested the appropriateness of the use of Coob-Douglas or the translog functional form for the different data sets namely SRI, CRPS, and Pooled. The study used the likelihood ratio LR test. LR calculated (LRc) = -2(ln LR restricted – ln LR unrestricted), if LRc > LR tabulated, the null hypothesis (H_0) is rejected. The first hypothesis reveals that the translog model is more appropriate for the SRI and the pooled data. The Cobb Douglas CD is suitable for the CRPS sample.

The second hypothesis has tested the justification of the use of the stochastic frontier model. The result depicts that the inefficiency component is absent from the error term for the SRI and pooled samples. The deviation of the output from the frontier is mainly due to the noise effects. So, the OLS is more suitable than the stochastic frontier model. However, the null hypothesis of no inefficiency component in the model is rejected for the CRPS sample. This indicates the presence of inefficiency component in the model. Therefore, the stochastic frontier model is more appropriate than the OLS with normal error for CRPS sample.

The third hypothesis tested the absence of inefficiency effect in the model. The results show that the inefficiency effects are absent from SRI and the pooled data. However, the null hypothesis is rejected for the CRPS. This implies the presence of inefficient effects on these farms.

The fourth hypothesis tested the non-influence of exogenous factors on the variation of efficiency level. The results demonstrate that the exogenous factors do not influence the variation in the level of efficiency for SRI, CRPS, and pooled data.

The result of the fifth hypothesis testing the exhibition of constant return to scale (CRS) with the farms of the three groups of data indicate that SRI and pooled data do not exhibit CRS. CRPS data exhibit CRS.

Table 2. Results of hypotheses tested

Hypothesis	LR statistic (λ)	LR critical (x^2 0.001/mixed x^2 0.001)	Decision	Conclusion
1. $H_0:\beta_{ij} = 0^a$; $H_1:\beta_{ij} \neq 0^a$				
SRI	64.690	46.8	H_0 rejected	Translog is adequate
CRPS	42.415	46.8	H_0 we fail to reject	CD is adequate
Pooled	165.896	46.8	H_0 rejected	Translog is adequate
2. $H_0:\gamma = 0$; $H_1:\gamma = 0$				
SRI		0.848[b]	H_0 we fail to reject	OLS not frontier
CRPS		0.000[b]	H_0 rejected	Frontier not OLS
Pooled		1.000[b]	H_0 we fail to reject	OLS not frontier
3. $H_0:\gamma = \delta_0 = \delta_1 ... \delta_7 = 0$; $H_1:\gamma = \delta_0 = \delta_1 ... \delta_7 \neq 0$				
SRI	-0.222	25.37	H_0 we fail to reject	Inefficient not present
CRPS	27.148	25.37	H_0 rejected	Inefficient present
Pooled	-0.007	25.37	H_0 we fail to reject	Inefficient not present
4. $H_0:\gamma = \delta_1 = \delta_2 ... \delta_7 = 0$; $H_1:\gamma = \delta_1 = \delta_2 ... \delta_7 \neq 0$				
SRI	-3.559	24.32	H_0 we fail to reject	Factors not influence
CRPS	0	24.32	H_0 we fail to reject	Factors not influence
Pooled	-0.005	24.32	H_0 we fail to reject	Factors not influence
5. $H_0:\Sigma\beta_i = 1$; $H_1:\beta_i \neq 1$				
SRI		0.035[c]	H_0 rejected	not CRS
CRPS		0.349[c]	H_0 we fail to reject	Exhibit CRS
Pooled		0.023[c]	H_0 rejected	not CRS

Note. [a] Bij = 0 means the Cobb-Douglas is the appropriate functional.

[b] The value of the probability of z testing the inefficiency component.

[c] The value of the probability of chi2 testing the constant return to scale CRS.

Source. Author from data.

3.3 Estimation of Parameters of the Stochastic Frontier and Meta Frontier Model

Table 3 shows the results of the estimates of stochastic frontier and meta frontier model. The labor positively affects the production of SRI rice while organic manure and its square are negatively linked to SRI rice production. The organic manure is monotonic. They are both statistically significant at 5% and the square of organic manure is significant at 1%. SRI rice production will increase by 0.4% as a result of a one percent increase in labor. This result is in line with the findings of (Koirala, Mishra, & Mohanty, 2014) but contrary to the findings of (Vasanthi, Sivasankari, & Gitanjali, 2017).

This result could be explained by the fact that SRI is labor intensive technology. One of the principles of SRI is to transplant the seedling much earlier. During that period, most of the SRI farmers face labor rationing. This rationing is the main reason for the non-adoption of SRI by lots of farmers. SRI rice production will reduce by 0.1% as a result of a one percent increase in organic manure. This result could be explained by the fact that the effect of organic manure on the field is automatic. If you apply the organic manure in your field this year, your next year yield will be high compared to this year citrus paribus. The monotonic effect of organic manure simply means that keeping increase the application of organic manure, the SRI rice production will continue to decrease.

The inorganic fertilizer and land positively influence CRPS rice production while the use of other inputs negatively affects CRPS rice production. They are significant statistically at 1%. CRPS rice production will increase by 0.3% and 0.8% respectively as a result of 1% of inorganic fertilizer and 1% of land while it will decrease by 0.01% as result of 1% increase of other inputs. The positive link between inorganic fertilizer and CRPS rice production could be explained by the fact that the soil is able to provide the nutrient to rice plants need to exhibit their potential. The positive link between the land and CRPS rice production could be explained by the agricultural extensification. The increase in production is usually achieved in Sub-Saharan Africa through the increase in land cultivated. This result confirms the finding of Coulibaly et al. (2017) and Audibert (1997) who found that rice production highly depended on changes in the land at "*office du Niger*" in Mali. This result also supports the findings of Koirala et al. (2014). Other inputs include water, herbicide, and insecticide. Vasanthi et al. (2017) also found that an increase in pesticide cost leads to reduction in rice yields.

All the input variables are positively linked with the pooled data in the meta-frontier analysis except the organic manure. While only the variables other inputs and land influence positively the pooled data in the stochastic frontier analysis. The increase seed variable increases the rice paddy production up to a turning point beyond which the rice paddy production will fall with both pooled data analysis even though the variable seed square is not statistically significant for pooled data in the stochastic frontier analysis.

The cross variable organic fertilizer and land is positively associated with SRI, Pooled stochastic frontier, and the meta frontier. While simultaneous increase in wage and land leads to reduce rice production under SRI, pooled stochastic frontier, and the pooled stochastic frontier. Inorganic fertilizer and land has adverse effect on the pooled stochastic frontier, and the pooled stochastic meta-frontier. Seed and land, and organic fertilizer and seed adversely affect rice production under SRI, and the pooled stochastic frontier.

The down part of the Table 3 shows the value of lambda which is the relation between the variance of the technical efficiency u_i and the noise error v_i. A value of lambda significantly greater than one means that the deviation of the output from the frontier is mainly due to the inefficiency component. When lambda is less than one, the deviation of the output from the frontier is mainly due to the noise error. The value of lambda is greater than one in all our estimationst (SRI, CRPS, and pooled stochastic meta-frontier) except that of the pooled stochastic frontier. However, the technical inefficient component was significant only for SRI which suggests that the exogenous factors are unable to account for inefficiency for the other data sets.

Table 3. Parameter estimates from stochastic frontier (SRI, CRPS, and Pooled) and stochastic meta-frontier (SMF)

Variables	Variable Description	SRI	CRPS	Pooled	SMF
Totalabor	Cost of both hired and family labor	0.440** (0.190)	0.002 (0.094)	0.092 (0.085)	0.306*** (4.19e-06)
Orgfert	Quantity of organic manure in kg used per season	-0.137** (0.067)	-0.048 (0.039)	-0.043 (0.030)	-0.084*** (1.82e-06)
Otherinput	Cost of (water+herbicide+insecticides per season)	0.079 (0.051)	-0.015*** (0.005)	0.046* (0.025)	0.043*** (1.36e-06)
Seedcost	Cost of seed used (price*quantity)/kg/season	0.008 (0.115)	0.007 (0.016)	-0.066 (0.045)	0.015*** (2.76e-06)
Infertcost	Cost of fertilizer (NPK+DAP+UREA) used per season	0.101 (0.245)	0.344*** (0.092)	0.135 (0.082)	0.401*** (4.85e-06)
Land	Land used for rice cultivation in hectares	0.395 (0.261)	0.788*** (0.067)	0.824*** (0.078)	0.410*** (2.92e-06)
WAGETOT2	Interation term for labor with itself	0.307 (0.721)		-0.021 (0.287)	1.163*** (2.90e-05)
ORGFERT2	Interation term for organic manure with itself	-0.086*** (0.027)		-0.045* (0.025)	-0.055*** (1.50e-06)
OTHERINP2	Interation term for other inputs with themself	0.019 (0.014)		0.016** (0.007)	0.017*** (3.56e-07)
SEED2	Interation term for seed with itself	0.092 (0.062)		-0.020 (0.013)	-0.004*** (8.08e-07)
INORGFERT2	Interation term of inorganic fertilizer with itself	0.0367 (0.152)		0.419*** (0.156)	0.154*** (4.87e-06)
LAND2	Interation term for land with itself	1.221*** (0.264)		0.921*** (0.225)	1.158*** (8.58e-06)
WAGTOT*ORFFERT	Interation term for labor and organic manure	0.108 (0.077)		0.002 (0.050)	0.020*** (2.14e-06)
WAGTOT*SEED	Interation term for labor and seed	0.290* (0.164)		-0.061 (0.069)	0.074*** (5.78e-06)
WAGTOT*OTHERINP	Interation term for labor and other inputs	-0.011 (0.047)		0.002 (0.013)	0.047*** (7.06e-07)
WAGTOT*INORFERT	Interation term for labor and inorganic fertilizer	0.106 (0.232)		0.334* (0.189)	-0.282*** (8.75e-06)
WAGTOT*LAND	Interation tem for labor and land	-0.691** (0.325)		-0.376* (0.193)	-0.901*** (1.5 9e-05)
ORFFERT*SEED	Interation term for organic manure and seed	-0.054*** (0.017)		-0.006 (0.0151)	-0.006*** (9.14e-07)
ORFFERT*OTHERINP	Interation term for organic manure and other inputs	-0.002 (0.009)		-2.46e-05 (0.004)	-0.008*** (1.82e-07)
ORFFERT*INORFERT	Interation term for organic manure and inorganic fertilizer	0.027 (0.037)		-0.015 (0.039)	0.061*** (1.51e-06)
ORFFERT*LAND	Interation term for organic manure and land	0.083* (0.050)		0.094** (0.045)	0.063*** (1.44e-06)
SEED*OTHERINP	Interation term for seed and other inputs	0.009 (0.011)		2.55e-05 (0.006)	0.006*** (3.08e-07)
SEED_INORFERT	Interation term for seed and inorganic fertilizer	-0.007 (0.055)		9.13e-05 (0.052)	0.050*** (2.60e-06)
SEED_LAND	Interation term for seed and land	-0.327*** (0.100)		0.007 (0.053)	-0.133*** (3.40e-06)
OTHERINP_INORFERT	Interation term for other inputs and inorganic fertilizer	0.008 (0.026)		0.001 (0.013)	0.023*** (8.52e-07)
OTHERINP_LAND	Interation term for other inputs and land	-0.048 (0.043)		-0.018 (0.013)	-0.081*** (8.55e-07)
INORFERT_LAND	Interation term for inorganic fertilizer and land	-0.092 (0.123)		-0.544*** (0.154)	-0.005*** (4.92e-06)
Sigma u		0.6*** (0.2)	5.43 (3.7)	0.002 (0.01)	0.63 (0.68)
Sigma v		0.08*** (0.008)	0.15*** (0.02)	0.06*** (.003)	1.50e-09 (1.51e-07)
Lambda		7.44*** (0.2)	3.71*** (35.3)	0.04** (0.013)	4.19e+08*** (0.68)

Note. Standard errors in parentheses and ***, **, * represent statistical significance level respectively at 1%, 5%, and 10%.

3.4 Estimation of Technical Efficiency and Technology Gap Ratios

Table 4 summarizes the result of the technical efficiency from stochastic frontier (TE), meta frontier (TE*) and technology gap ratio (TGR). The results indicate that the mean technical efficiency from the stochastic frontier with respect to group frontiers are equal to 0.96 and 0.79 for SRI and CRPS. This implies that on average SRI farmers are operating at 4% below their group frontier, whilst the CRPS farmers are operating at 21% below their group frontier. For these rice farmers (SRI, CRPS) to be 100% technically efficient, they will need to bridge the gap between their current output and the maximum potential output of their systems by addressing the factors that cause inefficiency. The mean technical efficiency relative to meta-frontier for SRI and CRPS are respectively 0.95 and 0.88 for SRI and CRPS farmers. This implies that on average, SRI farms are more technically efficient than those farms operating under CRPS.

Furthermore, the mean technology gap ratio is 0.98 and 0.91 for SRI and CRPS farmers, respectively. These results show that if the SRI farmers were technically efficient, they could have increased their production by closing the gap of 2% while the CRPS farmers could have increased their production by closing the gap of 9%. This implies that the CRPS farmers in Mali are distant to meta frontier than their SRI counterparts. This further

indicates that the SRI farmers will reach the maximum potential output for rice production in Mali faster than CRPS farmers if all factors are maintained constant. This finding is contradictory with Onumah et al. (2013). These authors compared the organic cocoa farming to conventional cocoa farming, they found that conventional cocoa farmers are more technically efficient with high technology gap ratios compared to the organic cocoa farmers.

Table 4. Technical efficiency scores and technology gap ratios

Index	SRI	CRPS	Rice industry
Technical efficiency TE (stochastic frontier)			
Mean	0.964	0.792	0.858
Min	0.597	0.096	0.091
Max	0.986	0.952	0.972
SD	0.040	0.164	0.136
Technical efficiency TE* (metafrontier)			
Mean	0.946	0.879	0.913
Min	0.754	0.536	0.536
Max	1	1	1
SD	0.530	0.103	0.088
Technology gap ratio TGR			
Mean	0.985	0.918	0.999
Min	0.784	0.102	0.575
Max	1	1	1
SD	0.089	0.244	0.796

4.5 Determinants of Technical Inefficiency

Table 5 presents the results of the inefficiency model. The results indicate that only the age of farm decision maker has positive and significant influence on technical inefficiency for the CRPS. In the case of SRI farmers, gender, age of farm decision maker, education, experience in rice farming, training and flooding level have influence on the technical inefficiency. More explicitly, age of farm decision maker, education, experience in rice farming and traning have a positive and significant influence on inefficiency of SRI farms This implies that the increase of these factors will increase the inefficient level. But gender, family members and flooding level have negative and significant influence on technical inefficiency. This could be explained by the fact that family members are more likely to work harder than the hired labor and also male effort are greater determinants than female in doing farm work. The positive relationship between the flooding level and the inefficient level under SRI practices could be explained by the fact that SRI practices do not require continuous flooding but rather intermittent irrigation. Even though rice is a semi-aquatic plant, increasing the flooding level would cause water stress and prevent the plant from optimal growth (SRI-RICE, 2012). Similar result is showed by the pooled sample about flooding level influence on technical efficiency. This result is similar to those found by Thibbotuwawa, Mugera, and White (2013), Mariano, Villano, Fleming, and Acda (2010). High educated people are more likely to participate in other activities than agriculture.

Table 5. Estimation of inefficiency model parameters

Variables	Pooled	SRI	CPRS
Farming system	0.148*** (0.038)		
Gender	0.001 (0.026)	-0.011** (0.005)	-0.004 (0.059)
Age of farm decision maker	-0.001 (0.001)	0.001** (0.001)	-0.004* (0.002)
Family members	-0.001 (0.002)	-0.003 (0.002)	-0.001 (0.002)
education	-0.001 (0.003)	0.004*** (0.001)	-0.007 (0.010)
Experience in rice farming	0.001 (0.001)	0.001* (0.000)	0.002 (0.002)
Training	-0.033 (0.039)	0.028* (0.016)	-0.045 (0.044)
Flooding level	-0.002* (0.001)	-0.002** (0.001)	-0.001 (0.001)
Constant	0.930*** (0.058)	0.921*** (0.020)	1.041*** (0.110)
Model Specification parameters			
Pseudo r-squared	-0.454	-0.105	-0.086
F-test	19.735***	6.263***	12.08*
Log-likelihood	151.200	206.324	44.176
N	208	104	104

Note. Standard errors in parentheses and ***, **, * represent statistical significance level respectively at 1%, 5%, and 10%.

4. Conclusion and Policy Recommendation

This study used the stochastic meta frontier approach to compare the efficiency level of the system of rice intensification and conventional rice production system in Mali using cross-sectional data of 208 farms. The Tobit estimation was applied to estimate the factors influencing the output oriented technical inefficiency The result shows that the mean technical efficiency and technology gap ratio estimated with respect to group frontier is in favor of SRI farmers. Therefore, the CRPS farms are more distant to the meta frontier, whereas the SRI farms are closer to the meta frontier. This implies that SRI farms are more technically efficient compared to CRPS farms. Therefore, SRI farmers are more likely to increase their output to meet the maximum potential output than CRPS farmers. The results also showed that the deviation of the output from the frontier is due to both inefficiency and noise components

The government could revitalize the extension service in order to train in best and innovative agricultural practices. The extension service could diffuse and improve the adoption of new technology in general and SRI adoption in particular in order to increase farmers yield and income and their food security status. The government could also subsidize a mechanization program to further increase rice farmers's efficiency. Moreover, the government could level the old farms and develop new land with irrigation and drainage facilities in order to attrack more young people, since their more technically efficient in SRI practices.

Finally, the study suggests the government to help building market and competitive price for SRI rice and inform both consumer and producer about the importance of SRI practices in terms of health and environment protection. This could increase the incentive of farmers to further adopt this new practice.

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Appendix A

Table A1. Rice production elasticities and returns to scale

Variables	SRI	CRPS	Pooled
Lntotalabor	0.44	0.002	0.092
Lnorgfert	-0.137	-0.048	-0.043
LnOtherinput	0.079	-0.015	0.046
Lnseedcost	0.008	0.007	-0.066
Lninfertcost	0.101	0.344	0.135
Lnland	0.395	0.788	0.824
RTS	0.893	1.078	0.988

Note. CRPS exhibits an increasing return to scale IRS while the SRI and Pooled samples express a decreasing return to scale DRS.

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