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To What Extent Does Modified System of Rice Intensification (SRI) Training Increase Productivity of Small-Scale Rice Cultivation in a Rain-Fed Area? Evidence from Tanzania

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Abstract

This study investigates the impact of modified System of Rice Intensification (SRI) training provided by a large-scale private farm on the performance of surrounding small-scale rice farmers in a rain-fed area in Tanzania. We found that the training effectively increases the adoption of improved rice cultivation practices, paddy yield, and profit of rice cultivation by small-holder farmers. In fact, the trainees achieve paddy yield of 5 tons per hectare on average, which is remarkably high in rain-fed rice cultivation by any standard. Our results suggest high potential for achieving a rice Green Revolution in rain-fed areas and the importance of extension services by large-scale farms.

Keywords: Green Revolution, Sub-Saharan Africa, Technology Adoption, Lowland Rice, Modified System of Rice Intensification

JEL Classification: O12, O13, O33, O55, Q12, Q16, Q18

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Agricultural development is indispensable for poverty reduction and food security in Sub-Saharan Africa (SSA). Rice is considered one of the most important and promising crops on which to achieve technology transformation similar to a Green Revolution in Asia. This could lead to a drastic increase in paddy yield in SSA due to the diffusion of modern varieties with increased chemical fertilizer use (Seck et al. 2010; Otsuka and Larson 2013). In fact, fertilizer-responsive modern varieties developed in Asia have exhibited high yield potential in irrigated areas in SSA (Kajisa and Payongayong 2011; Nakano et al. 2013; Otsuka and Larson 2013). However, the irrigation ratio in SSA is much lower than in Asia (Johnson, Hazell and Gulati 2003; Hayami and Godo 2005). Since it takes time and resources to develop irrigation infrastructure, whether SSA can achieve a rice Green Revolution in the near future critically depends on the success in improving the productivity of rain-fed rice cultivation (Nhamo et al. 2013; Nakano, Kajisa and Otsuka 2014).

Recent case studies have shown that intensive training on rice cultivation can effectively enhance the adoption of new technologies including modern varieties (MVs) with the use of chemical fertilizer and improved agronomic practices such as dibbling, which have contributed to increased productivity of rice cultivation in both irrigated and rain-fed areas in SSA (Kijima, Ito and Otsuka 2012; De Graft-Johnson et al. 2014; Nakano, Kajisa and Otsuka 2014). However, improved rice cultivation technologies have not been widely adopted thus far, mainly because of a weak public extension system (Nakano, Kajisa, and Otsuka 2014). One possible solution for this problem is to utilize the private sector's management knowledge and resources in the form of contract farming (World Bank 2008). In contract farming, an agribusiness firm carries out processing and marketing but contracts out the actual farm production to peasant farmers. The firm often provides technical guidance, modern inputs, credit and other services to peasants in return for their pledged production to the firm (Key and Runsten 1999; Singh 2002; Hayami and Godo 2005; Wang, Wang and Delgado 2014).

In order to examine the potential impact of improved management practices on the productivity of rain-fed rice cultivation, the authors conducted a survey in Kilombero District in Tanzania, the largest rice producing country in East Africa. We selected villages in the neighborhood of Kilombero Plantation Limited (KPL) as our study site. KPL is a large-scale private rice farming company that provides training on improved rice cultivation practices to surrounding small-scale farmers. Although KPL's attempt to offer contract farming is still in its initial stage, this case would provide an opportunity for researchers to examine the potential impacts of private extension services on the productivity of small-scale farming.

The training is called the System of Rice Intensification (SRI); its main contents include the adoption of MVs, chemical fertilizer use, and straight-raw dibbling or transplanting with a spacing of 25cm by 25cm. Note that SRI here is a modified and simplified version of the well-known SRI developed in Madagascar, which does not require a new variety of rice or additional external inputs.[1] Thus, we call the package of technologies adopted in our study site the modified SRI (MSRI for short).

We collected two types of data. The first was plot-level recall data on paddy yield and the adoption of technologies for the past 4 years, which included data from both before and after the training. The second one was cross-sectional plot-level data on rice cultivation, which included detailed information on the use of current, labor, and capital inputs in 2013. It is relatively easy for the farmers to recall their technology adoption and harvest per unit of land for the past few years, while it is very difficult for them to remember all the details on input use. Thus, we constructed a recall panel data set for the former and cross section data set for the latter. The very unique feature of our data set is that some of our sample households cultivate rice in more than two plots by adopting MSRI technologies in one plot but not in others. This enabled us to examine the impact of technology adoption on paddy yield and profit of rice cultivation accurately. A remarkable finding is that trainees harvest as much as 5 tons of paddy per hectare under rain-fed conditions, which far exceeds not only the average paddy yield of 2 tons per hectare in SSA but also 4 tons per hectare in Asia.

The paper is organized as follows. Section 2 explains the study sites and data collection method, followed by the descriptive analyses in Section 3. Section 4 shows the results of the regression analyses on the impact of training on the adoption of improved rice cultivation technologies and paddy yield by using panel data. In section 5, we examine the impact of technology adoption on costs and profit of rice cultivation by using propensity score matching methods and sub-sample analysis with household-fixed effect with our cross section data. Section 6 concludes the paper.

Data and Study Site

Study Site

The survey was conducted in the nearby villages of a large-scale rice farming company, called Kilombero Plantation Limited (KPL). KPL was established in 2008 as a private rice farming company, with capital from England and the U.S., in Kilombero Valley, Kilombero District, Morogoro Region. The Kilombero Valley is about 400 km to the west of the country’s main city, Dar es Salaam, and covers an area of about 11,600 square kilometers. Rice cultivation is very popular among farmers in the valley, and they produced about 9% of all rice produced in Tanzania in 2003 (Kato 2007). KPL cultivates 5000 ha of paddy field, of which 215 hectares are irrigated by sprinkler. According to the manager of KPL, the average paddy yield in rain-fed areas of the farm is from 3.1 to 3.5 tons per hectare, while that in irrigated areas is 7 tons per hectare.

The land acquired by KPL used to belong to an estate. Around 1985, Korea Tanzania Agricultural Company (KOTACO), a state-owned joint venture of Tanzania and North Korea, was established in the area. However, due to management problems, KOTACO ceased operation by the mid-1990s. KPL started operation in 2008 and began offering extension services to local small-scale farmers in the surrounding villages in 2010. KPL procures a certain amount of paddy from trainees, but whether this is profit-oriented contract farming is not clear. The reason is that KPL offers extension service only at the request of the Tanzanian government, which was responding to the complaints of neighboring farmers that such a huge area is cultivated by a single large company.

The SRI office, which was established as a section of KPL, is in charge of extension services to the local farmers. They trained 25 farmers in a village in 2010 and expanded their extension service to 1350 farmers in 2011, 2850 farmers in 2012, and 2250 farmers in 2013. Currently, the extension services provided by the SRI office are financially supported by USAID and operate in 10 surrounding villages.[2] When they start the training program, SRI officers call for a village meeting and ask those who are interested in MSRI to form a group of 25 farmers. The criteria for the participants are that they must be residents in the villages, must be farmers, and must not have been trained by the SRI office before. A group of participants has to provide a quarter-acre piece of land, which is called a demo plot. The extension officers, who are qualified agronomists hired by KPL and USAID, provide training in the demo plot during the season. During the training, participants are provided with 26 kg of chemical fertilizer and 4 kg of seeds of a modern rice variety (called SARO5), which are recommended amounts for a quarter acre, and are required to cultivate a quarter acre of their own land following the technology and management practices taught by the training program.

One year after they receive training, instead of free modern inputs, trainees are eligible to receive in-kind credit of chemical fertilizer and seed from NGOs that are associated with the SRI office. NGOs provide the credit of 440,000 Tanzanian Shillings (Tsh) for an acre in cash before the cultivation starts. Out of this 440,000 Tsh, 200,000 Tsh is deducted for the purchase of 100 kg of chemical fertilizer, 12 kg of seeds, and the rental cost of a rotary weeder. This leaves 240,000 Tsh remaining in the hands of the farmers. Farmers are obliged to repay 15,000 Tsh every two weeks during the cultivation season for 5 months, resulting in 10 installments. In addition, farmers need to sell 6 bags (approximately 600 kg) of paddy yield at the agreed price to KPL at the time of harvest, so that KPL can repay its remaining balance to the lending NGOs.

However, this credit service has not been popular among farmers. First, it is difficult for the farmers to repay the loan every two weeks during the cultivating season, as they generate most of their cash income at harvest time. Furthermore, there is sometimes disagreement over the selling price of the rice between farmers and KPL. For example, some farmers refused to sell at the agreed price to KPL in 2012, when they observed that the market price was higher than the agreed price at the time of the harvest. On the other hand, in 2013, due to the government ban on rice export, the price of paddy rice decreased significantly at the harvesting season, which caused serious loss to KPL. Such fluctuation in price caused conflicts between the farmers and KPL. As a result, this credit service (or "contract farming") of KPL does not seem to be widely accepted by the farmers. In fact, only 11 households out of 25 eligible farmers received the loan from NGOs associated with KPL in 2013. Note, however, that conflict between farmers and a large firm is not an exceptional case in contract farming, and is observed in other areas as well (Singh 2002; Barrett et al. 2012).

Sampling

In order to examine the impact of the training program, we selected three villages where training was held (we call them training villages hereafter). We also covered two nearby villages where no training was held (we name them non-training villages). Training villages and non-training villages were adjacent and in a similar agro-ecological condition. In each training village, we interviewed on average 37 training participants and 35 non-participants. In addition, we interviewed on average 35 farmers per village in non-training villages, generating the total sample size of 283 households.[3]

During the interviews, we asked farmers to list all of their farming plots. Among those listed, we selected two paddy plots for plot-level analysis. Note that, in our study sites, trainees clearly differentiated between plots where they adopted MSRI technologies as a package (called MSRI plots) and plots where they did not adopt these technologies at all (called non-MSRI plots). Since MSRI technologies are newly introduced and highly labor intensive, farmers cultivate at most one plot by using

MSRI technologies. For sample farmers who grow rice with MSRI technologies, we automatically selected that MSRI plot and selected another plot randomly where rice is grown with traditional cultivation methods. For sample farmers who have not adopted MSRI technologies, we randomly selected up to two plots where rice is grown. We collected information on detailed rice cultivation practices and input use in the sample plots for the cultivation season of 2013, generating 406 sample plots of 283 households. After dropping households and plots with missing values in key variables, total sample size became 398 plots of 281 households. We also collected recall data on paddy yield and the adoption of key technologies from 2010 to 2013 so that we could construct a panel data set before and after the training. The sample size of our panel data was 398 plots of 281 households for 4 years, generating the total sample size of 1351 plots. Note that our sample is not balanced because some farmers do not grow rice in some years.[4]

Out of 110 training participants in our sample, no farmers were trained before 2011, 25 farmers were trained in the main season of 2012, and 85 farmers were trained in 2013. This implies that 25 farmers trained in 2012 and 85 trainees in 2013 received free inputs for a quarter acre from KPL in 2012 and 2013, respectively, while 25 trainees in 2012 were eligible for the KPL credit program in 2013. Since trainees in

2012 and 2013 received different services from KPL in 2013, we recognize the difference in impacts of the training on the farming of trainees in different years in the following analyses. Note that the impact of the MSRI training in 2013 for trainees in 2012 partially includes the impact of the credit service. Since only 11 out of 25 eligible farmers joined the credit program, it is difficult for us statistically to distinguish the effects of training and credit.

Descriptive Analyses

This section descriptively examines the impact of the training on the adoption of MSRI technologies and productivity of rice farming. Table 1 compares the adoption of modern inputs and improved practices by trainees in 2012, trainees in 2013, non-trainees in training villages, and farmers in non-training villages in 2013. The most important finding is that trainees, regardless of their training year, achieved as high a yield as 5 tons per hectare on average on their MSRI plots. This yield is remarkably high compared with the average paddy yield of 1.8 tons per hectare in other rain-fed areas in Tanzania (Nakano, Kajisa, and Otsuka 2014) and non-trainees' yield in the training village of 2.6 tons per hectare, suggesting the high yield potential of improved technologies in rain-fed areas.

This high yield may be attributed to the high adoption rate of new technologies by trainees on their MSRI plots. The adoption rate of MVs is as high as 97.1%, that of straight-row dibbling 82.5%, and that of wide spacing 59.2%. Trainees apply much more chemical fertilizer (91.8 kg per hectare) on MSRI plots than on their non-SRI plots (11.2 kg per hectare). Note also that there is no significant difference in the performance between trainees in 2012 and 2013, suggesting that this high yield and high rate of technology adoption continues even after KPL stops providing free inputs. Another important finding is that we do not observe significant difference between yields on the MSRI plots before training (2009–2010) and on other categories of the plots, suggesting that farmers do not necessarily select plots of good quality to adopt MSRI technologies. Lastly, the adoption of technologies and yield does not differ much between non-SRI plots of trainees and non-trainees in training villages (denoted as d-g) or between non-SRI plots of trainees and plots in non-training villages (denoted as d-h). These observations suggest that there is limited spill-over effect from trainees to non-trainees in training villages and also from MSRI plots of trainees to their non-SRI plots. However, slightly higher application of chemical fertilizer on non-SRI plots of trainees than on plots of non-trainees suggests the positive effects of better access to credit on fertilizer use.

In order to examine differences in the cost and benefits of rice production among farmers, we show factor payments by training status in table 2. We define income as gross output value minus paid-out costs of current inputs, hired labor, and rented machinery and draft animals. Profit is defined as income minus imputed costs of family labor and owned capital, evaluated at the village median wage and rental rate; it can be interpreted as the return to land and management ability. Imputed value of free inputs provided by KPL is also included as input costs.

Trainees achieve much higher gross output value on their MSRI plots (1061.9 USD per hectare) than on their non-SRI plots (632.0 USD per hectare). Furthermore, their gross output value is much higher than that of non-trainees in training villages or farmers in non-training villages. Since MSRI technologies are labor and current inputs intensive, trainees pay higher labor and current input costs on their MSRI plots. Especially, imputed family labor cost is much higher in the MSRI plots of trainees (345.1 USD per hectare) than in other categories of the plots. This suggests that MSRI technology is more family-labor intensive as it requires more care and judgment than traditional cultivation methods. Despite the increase in labor and other input costs, however, the increase in gross output value exceeds that in costs and, hence, trainees achieve higher income and profit per hectare on MSRI plots than on other categories of plots. Note also that there is no significant difference in income and profit between non-SRI plots of trainees and non-trainees in training villages, which are shown in columns (d) to (g) in table 2. Income and profit on non-SRI plots of trainees are also not higher than those in non-training villages, as shown in columns (d) through (f) and (h).

Impact of Training on Technology Adoption and Paddy Yield

Methodology and Variable Construction

In this section, in order to investigate the impact of MSRI training on the adoption of rice cultivation technologies and paddy yield, we estimate the difference-in-differences model by using recall panel data (Imbens and Wooldridge 2007). The dependent variables are paddy yield (tons/ha) and the sets of technology adoption variables including the dummy variable, which takes 1 if a farmer adopts MV, dibbling or transplanting in rows; a recommended spacing of 25 cm by 25 cm; and chemical fertilizer use (kg/ha). The base model is：

$$
\begin{aligned}
y_{vijt} &= \tau(MSRI_{vij} * trainee_{it} * post-training_{it}) \\
&+ \delta(trainee_{it} * post-training_{it}) + \theta Year + p_{vij}\gamma + u_{vijt}
\end{aligned}
\qquad (1),
$$

where

y_{vijt}: the outcome variable of individual i's plot j in the village v at time t,

$MSRI_{vij}$: time-invariant dummy variable that takes 1 if the plot is used as an MSRI plot in any single year,

$trainee_{it}$: dummy variable that takes 1 if the cultivator of the plot has attended MSRI training in either 2012 or 2013,

post-training$_{it}$: year 2012 dummy for 2012 trainees and year 2013 dummy for trainees in 2012 and 2013,

Year: year dummies,

p_{vij}: plot-specific time-invariant characteristics, and

u_{vijt}: error term.

The most important independent variable is the interaction term of the MSRI plot, trainee dummy, and post-training dummy, which is intended to measure the impact of MSRI training. Note that the MSRI plot dummy here is a time-invariant dummy variable that takes 1 if a plot is used as an MSRI plot in any single year. We include post-training dummies (i.e., year 2012 dummy for trainees in 2012 and year 2013 dummy for trainees in 2012 and 2013) because trainees have attended the training by these years. In order to examine the differential impact of the training in 2012 and 2013, we constructed three interaction terms: (1) the interaction term of MSRI plot dummy, 2012 trainee dummy and year 2012 dummy; (2) the interaction term of MSRI plot dummy, 2012 trainee dummy and year 2013 dummy; and (3) the interaction term of MSRI plot dummy, 2013 trainee dummy and year 2013 dummy. Since there are only three households who gave up MSRI technologies after they adopted them, we consider the coefficient τ as the estimator of the impact of the training.

We also include the interaction terms of the trainee dummy and the post-training dummy. The coefficient δ captures the impact of the training on productivity and technology adoption in non-SRI plots of the trainees due to their labor reallocation from non-SRI plots to MSRI plots or the positive spill-over effect of the training to the non-SRI plot of trainees. Again, in order to estimate the impact of training on the trainees in 2012 and 2013 separately, we include the interaction term of 2012 trainee and year 2012 dummy, that of 2012 trainee and year 2013 dummy, and that of 2013 trainee and year 2013 dummy. We estimate this model using the plot fixed-effect model.[5,6] By estimating the plot fixed-effect model, we can control for plot-specific time-invariant characteristics (p_{vij}) that may affect a farmer's endogenous selection of the MSRI plot. We include year dummies to capture the effects of general trends including non-trainees in both training and non-training villages.

Regression Results

Table 3 shows difference-in-differences estimation results of training impacts on paddy yield and technology adoption with plot fixed effects. All three interaction terms of the MSRI plot dummy, trainee dummy, and post-training dummy have positive and significant coefficients in all the regressions except for the chemical fertilizer use of 2012 trainee in 2012, suggesting the significant effects of the training. Compared to those of the non-trainees' plots, the trainees' adoption rates are higher on the MSRI plot by 0.6–0.9 for MV, by 0.3–0.9 for transplanting/dibbling in rows, and by 0.5–0.6 for recommended spacing. The trainees also increased chemical fertilizer application by 91–98 kg per hectare in 2013. As a result, trainees' paddy yield increases by 1.5–2.0 tons per hectare on the MSRI plot. Note that trainees in 2012 received free inputs in 2012 and trainees in 2013 received the same in 2013, while trainees in 2012 were eligible for the credit program instead of receiving free input in 2013. However, the difference between estimated coefficients on paddy yield of the interaction terms of the MSRI plot dummy, year 2012 trainee dummy, and year 2012 dummy (indicated as a) and that of the MSRI plot dummy, year 2012 trainee dummy, and year 2013 dummy (indicated as b) is not statistically significant, as the *F*-test shown below the table indicates. This result implies that the training was effective even after KPL stopped providing free inputs for the trainees. We also do not observe statistically different impact of MSRI training on paddy yield and technology adoption on MSRI plots between 2012 trainees and 2013 trainees in year 2013 (denoted as b and c in the table).

Impact of Technology Adoption on Costs and Profit

Methodology

In this section, we estimate the impact of the adoption of improved technologies on paddy yield, costs, and profit of rice cultivation by using our cross-section data in 2013. We apply two estimation methods: average treatment effect on the treated (ATT) by using Propensity Score Matching (PSM) and sub-sample analyses by using the plot-level variation of the adoption of MSRI technology (Wooldridge 2010; Takahashi and Barrett 2014).

First, we estimate the ATT of the adoption of MSRI technologies on paddy yield, costs, and profit of rice cultivation. Let y_{1j} denote an outcome of interest in plot j with MSRI adoption, and y_{0j} the outcome in the same plot without adoption. Let the variable D_j be a binary treatment indicator, where $D_j=1$ denotes an MSRI plot and $D_j=0$ otherwise. ATT can be defined as:

$$ATT = E(y_{1j} - y_{0j} \mid D_j = 1) = E(y_{1j} \mid D_j = 1) - E(y_{0j} \mid D_j = 1), \qquad (2)$$

where $E(\cdot)$ denotes an expectation operator. A fundamental problem here is that we cannot observe both y_{1j} and y_{0j}, as a plot cannot be in both states.

As is well known, simple comparison between MSRI plots and non-SRI plots would result in a biased estimation due to the endogeneity of technology adoption. In order to circumvent this problem, this paper relies on the PSM method proposed by Rosenbaum and Rubin (1983). PSM relies on an assumption of conditional independence, which means that conditional on the probability of using MSRI on a plot given observable covariates, an outcome of interest in the absence of treatment y_{0j} and MSRI adoption D_j is statistically independent. Another important assumption is called overlap assumption and can be expressed as $0 < \Pr(D_j = 1 | x_{ij}) < 1$, where $\Pr(D_j = 1 | x_{ij})$ denotes the probability of being an MSRI plot given household- and plot-level observable characteristics x_{ij} (Wooldridge 2010). If these two assumptions hold, then we can consistently estimate

$$ATT^{PSM} = E\left[y_{1j} \mid D_j = 1, p(x_{ij})\right] - E\left[y_{0j} \mid D_j = 0, p(x_{ij})\right] \qquad (3).$$

The major limitation of PSM is that if unobservable factors affect adoption decisions, then estimated ATT may be biased by selection effect of those unobservable factors. It is virtually impossible, however, to control for all the unobservable characteristics. Therefore, we test whether unobservables might affect our estimation results by using sensitivity tests (Rosenbaum 2002). Furthermore, we also check the robustness of our results by estimating ATT by using both Kernel matching and bias-corrected Nearest Neighbor matching methods.

As we discussed earlier, some households in our sample utilize some of their plots for growing rice by using MSRI technologies and other plots for growing rice in a traditional manner. In order to control for the unobserved household characteristics that cannot be controlled in the PSM estimation, we utilize this variation at the plot level to estimate the impact of the adoption of MSRI technologies on paddy yield, costs, and profit of rice cultivation by controlling household fixed effects. The advantage of this method is that we can control household innate characteristics that may affect both adoption of MSRI technologies and outcome variables, resulting in endogeneity bias in estimated coefficients. The drawback, however, is that we need to restrict our sample to 76 trainees whose data for both MSRI and non-SRI plots are available in 2013.

Regression Results for Average Treatment Effect on Treated of MSRI Adoption

In order to estimate the ATT of MSRI adoption, we first estimate the plot-level MSRI adoption function by using the probit estimation method, whose results are shown in appendix table 1. Using the estimation results of the probit model, we compute the propensity score for each plot. Note that we dropped four observations that do not satisfy the overlap assumption.[7]

Table 4 shows the ATT estimates of the impact of being an MSRI plot on productivity, production costs, and profit. For robustness check, we show the estimated results based on Kernel matching and biased-corrected Nearest Neighbor matching methods. We use an Epanechnikov kernel with a bandwidth of 0.06 and obtain standard error by bootstrapping with 500 replications for our Kernel matching estimation. The estimated coefficients are largely the same regardless of the matching methods, suggesting the robustness of our results. Yields in MSRI plots are higher than non-SRI plots by 2.2–2.4 tons per hectare. These estimates are somewhat larger than those reported in table 3. The family labor costs are significantly higher on MSRI plots than on non-SRI plots, while there is no significant difference in hired labor costs, suggesting that MSRI technologies are more family labor-intensive.[8] Despite its higher purchased input and labor costs, the increase in gross output value exceeds that in costs and, hence, cultivators achieve higher income and profit on MSRI plots than on non-SRI plots. ATT estimation results show that the profit on MSRI plots is higher than that on non-SRI plots by 245.3–265.8 USD per hectare, which is five times larger than the profit on non-SRI plots (52.6 USD per hectare).

In table 4, we also report the results for Rosenbaum bounds tests for sensitivity analysis (Rosenbaum 2002). We report the value of odds ratio of MSRI use, which alters the results of our statistical inference at the 10% level. Although there is no clear-cut critical threshold that distinguishes existence and non-existence of hidden bias, the larger the critical value is, the less sensitive to bias based on selection on unobservables our estimated results are (Rosenbaum 2002; Takahashi and Barrett 2014). Our results show that odds ratio to alter the inference is from 1.9 to 7.7, suggesting that our results are not sensitive to unobserved characteristics.

Regression Results for Household Fixed-Effect Models on Impact of MSRI

Table 5 shows the estimation results of sub-sample analyses with household fixed effects on the impact of MSRI adoption on paddy yield, costs, and profit of rice cultivation in 2013. We separately include the interaction term of trainee in the 2012 dummy and MSRI plot dummy, and that of trainee in the 2013 dummy and MSRI plot dummy. Note that the sample is restricted to trainees who cultivated both MSRI plots and non-SRI plots in 2013. The results show that the adoption of MSRI increases the paddy yield by 2.4–2.6 tons per hectare. Although total labor costs and input costs increase, the increase in gross output value exceeds that of costs, and trainees earn higher income by 449–533 USD and profit by 286–393 USD per hectare in MSRI plots than in non-SRI plots. These results are consistent with the average treatment effects reported in table 4. Note that family labor cost is significantly higher, while hired labor cost is lower in MSRI plots than in non-SRI plots. This result suggests that farmers cannot rely on hired labor to adopt MSRI technologies, probably due to its care-intensive feature and the high monitoring cost of hired agriculture labor (Otsuka 2007).

Furthermore, the estimated coefficient on profit is larger for trainees in 2012 than for trainees in 2013, suggesting that 2012 trainees achieved at least as high a profit as those in 2013. This result suggests that training is effective in raising profit even after KPL stops providing free inputs, partly because trainees in 2012 enjoyed being eligible for the credit program and partly because of the learning effect.

Conclusion

This paper examined the impact of the management training provided by a private company in a rain-fed rice cultivating area in Kilombero District in Tanzania. The most important finding is that productivity and profitability of rice cultivation is much higher when improved technologies are adopted, even under rain-fed conditions. We found that the training effectively enhances the paddy yield by 1.7–2.6 tons per hectare and the profit by 245.3–393.4 USD per hectare, even though family labor costs increase. As a result, the farmers who apply recommended MSRI technologies achieve as high a yield as 5 tons per hectare on average. Given that the average paddy yield in other rain-fed areas of the country is merely 1.8 tons per hectare (Nakano, Kajisa and Otsuka 2014), and the average yield without new technology adoption in the study sites is 2.6 tons per hectare, this is a remarkably high yield. Note also that, according to the manager of KPL, the paddy yield in the large-scale farm of KPL is about 3.1–3.5 tons per hectare. These observations suggest that the small-scale farmers are more productive than a large-scale farm as long as such farmers are provided with proper technologies and generous credit.

Judging from the much higher income as well as profit per hectare in MSRI plots than in non-SRI plots, the new technologies have the potential to be disseminated rapidly and widely to many other peasant farmers in the Kilombero Valley. If that happens, it is not a dream that the Kilombero Valley, which is as large as 11,600 km^2, could become the center of rice production in East Africa. However, since this project is at its inception stage, it is too early to judge the scalability of the MSRI. Since it is extremely labor intensive, particularly for planting and weeding, many farmers may not want to adopt or expand MSRI plots unless labor markets develop.

Our results also suggest that private extension service by a large-scale farm can effectively enhance the productivity of small-scale rice farmers. However, we have to be careful in judging the sustainability and scalability of this type of private extension to other areas. As we discussed earlier, the offer of credit service and fixed product price (or “contract farming”) by KPL was not widely accepted by farmers because of the fluctuation in the market price for paddy rice. Currently, the extension service is financially supported by USAID. Whether private companies have incentive to provide qualified extension services critically depends on whether they can develop mutually beneficial relationships with small-scale farmers. We need to further examine if this mutually beneficial collaboration will be expanded to other vast but under-utilized rain-fed areas in SSA.

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Table 1. Yield and Adoption of Modern Inputs and Improved Practices in the Sampled Rice Plots in 2013 by MSRI Training Participation

	Training village							Non-training village	Average	Difference[2]					
	Trainee						Non-trainee								
	MSRI plot in 2013			Non-SRI plot in 2013											
	Average	2012 trainee	2013 trainee	Average	2012 trainee	2013 trainee				(a)-(d)	(d)-(g)	(g)-(h)	(d)-(h)	(b)-(c)	(e)-(f)
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)							
Paddy yield in 2013 (tons per hectare)	5.1	5.3	5.0	2.8	2.9	2.8	2.6	2.9	3.3	2.3***	0.2	-0.3**	-0.1	0.3	-0.1
Average paddy yield before training (2009–2010) (tons per hectare)	2.7	2.8	2.7	2.6	2.6	2.6	2.3	2.3	2.5	0.1	0.3	0.0	0.3*	0.1	0.0
Modern inputs use in 2013															
Share of modern variety plots (%)	97.1	95.7	97.5	9.3	9.1	9.4	5.6	2.4	29.4	87.8***	3.7	3.2	6.9*	-1.8	-0.3
Chemical fertilizer use (kilograms per hectare)	91.8	104.1	88.3	11.2	19.1	8.5	2.5	2.5	27.5	80.6***	8.7**	0.0	8.7*	15.8	10.6
SRI adoption/improved practices in 2013															
Share of straight-row dibbling plots (%)	82.5	82.6	82.5	1.2	4.5	0.0	0.8	2.4	22.4	81.3***	0.4	-1.6	-1.2	0.1	4.5*
Share of straight-row transplanting plots (%)	7.8	8.7	7.5	0.0	0.0	0.0	0.8	1.2	2.5	7.8***	-0.8	-0.4	-1.2	1.2	0.0
Share of plots adopting spacing of 25cm x 25cm or more (%)	59.2	60.9	58.7	1.2	4.5	0.0	1.6	2.4	16.6	58.0***	-0.4	-0.8	-1.2	2.2	4.5*
Paddy plot size (ha)	0.4	0.5	0.4	1.1	1.3	1.0	0.9	1.2	0.9	-0.7***	0.2	-0.3*	-0.1	0.1	0.3
Observations (plots)	103	23	80	86	22	64	126	83	398						
Observations (households)	110	25	85				100	71	281						

Note: We asked farmers to list the usage of each of their farming plots. Among those listed, we selected two paddy plots for plot-level analysis. For farmers who grow MSRI rice, we automatically selected that plot where MSRI rice is grown and selected another plot randomly where traditional rice is grown. For farmers who do not grow MSRI rice, we randomly selected up to two plots where rice is grown.

*** denotes significant at 1%, ** significant at 5%, and * significant at 10% in *t*-test comparison between the labeled categories.

Table 2. Factor Payments in the Sample Rice Plots in 2013 by MSRI Training Participation

	Training village								Difference[2]				
	Trainee												
	MSRI plot in 2013			Non-SRI plot in 2013			Non-trainee	Non-training village					
	Average	2012 trainee	2013 trainee	Average	2012 trainee	2013 trainee			(a)-(d)	(d)-(g)	(g)-(h)	(d)-(h)	(b)-(c)
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)					
Gross output value (USD/ha) [1]	1061.9	1202.2	1021.5	632.0	659.5	622.6	618.1	732.6	429.9***	13.9	-114.5*	-100.6*	180.7
Paddy price (USD/kg)	0.203	0.208	0.202	0.223	0.217	0.225	0.236	0.225	-0.020	-0.013	0.011	-0.002	0.006
Hired labor cost (USD/ha)	173.6	215.1	161.7	232.6	326.4	200.3	149.6	140.3	-59.0	83.0**	9.3	92.3**	53.4
Imputed cost of family labor (USD/ha)	345.1	306.1	356.3	162.6	140.5	170.8	241.0	188.3	182.5***	-78.4**	52.7	-25.7	-50.2
Rented machine or animal cost (USD/ha)	82.8	90.7	80.6	40.5	32.6	43.2	91.2	89.9	42.3***	-50.7***	1.3	-49.4***	10.1
Imputed cost of owned machine or animal (USD/ha)	10.1	20.7	7.0	61.6	60.7	61.9	19.8	24.1	-51.5***	41.8***	-4.3	37.5***	13.7
Inputs cost (USD/ha)	118.1	124.4	116.3	53.1	58.6	51.2	70.2	59.8	65.0***	-17.1*	10.4	-6.7	8.1
Seeds (USD/ha)	37.8	27.3	40.8	32.3	32.7	32.1	48.3	28.8	5.5	-16.0	19.5*	3.5	-13.5
Chemical fertilizer (USD/ha)	59.4	70.8	56.1	6.9	11.6	5.3	2.0	2.0	52.5***	4.9*	0.0	4.9	14.7
Marketing and milling cost (USD/ha)	18.0	77.3	0.9	6.7	14.8	3.9	43.1	26.8	11.3	-36.4	16.3	-20.1*	76.4**
Rice income (USD/ha)	687.1	713.2	679.6	323.3	246.1	349.9	302.7	434.7	363.8***	20.6	-132.0**	-111.4**	33.6
Rice profit (USD/ha)	314.1	368.1	298.6	74.9	25.9	91.2	3.1	203.4	239.2***	71.8	-200.3***	-128.5**	69.5
Observations (plots)	103	23	80	86	22	64	126	83					
Observations (households)	110	25	85				100	71					

Note: The exchange rate used is USD 1 = TZS 1,583 (year 2013).

*** significant at 1%, ** significant at 5%, and * significant at 10% in *t*-test comparison between the labeled categories.

Table 3. Difference-in-Differences Estimator of Impact of MSRI Training on Yield, the Adoption of Modern Inputs, and Improved Practices in 2010–2013 (Plot Fixed Effect – Unbalanced Panel)

VARIABLES		Paddy yield (tons/ha)	Modern variety (=1)	Chemical fertilizer (kg/ha)	Dibbling/transplanting in row (=1)	Recommended spacing (=1)
		(1)	(2)	(3)	(4)	(5)
Effect on MSRI plot						
MSRI plot x	(a)	1.531**	0.621***	7.132	0.270*	0.449***
2012 Trainee x year 2012 dummy		(2.13)	(5.66)	(0.57)	(1.75)	(3.73)
MSRI plot x	(b)	2.008***	0.869***	91.183***	0.877***	0.591***
2012 Trainee x year 2013 dummy		(3.67)	(11.64)	(3.42)	(13.73)	(5.19)
MSRI plot x	(c)	1.621***	0.778***	97.226***	0.865***	0.526***
2013 Trainee x year 2013 dummy		(4.97)	(13.54)	(7.43)	(19.03)	(8.11)
Effect on non-SRI plot						
2012 Trainee x year 2012 dummy		-0.013	-0.041**	19.591**	0.223**	0.010
		(-0.03)	(-2.34)	(2.50)	(2.13)	(0.30)
2012 Trainee x year 2013 dummy		-0.202	0.059	20.364	0.009	0.003
		(-0.63)	(0.98)	(1.38)	(0.29)	(0.10)
2013 Trainee x year 2013 dummy		-0.258	0.074*	2.188	-0.027**	-0.024**
		(-1.39)	(1.82)	(0.65)	(-2.53)	(-2.28)
Year dummy						
2011		-0.033	0.017*	0.385*	0.001	-0.001
		(-0.59)	(1.65)	(1.65)	(1.38)	(-0.99)
2012		0.190**	0.054***	2.002**	0.034**	0.020
		(2.45)	(2.79)	(2.27)	(2.35)	(1.53)
2013		0.462***	0.035**	2.726***	0.032***	0.026**
		(4.38)	(2.08)	(2.67)	(2.82)	(2.36)
Constant		2.512***	0.008	-0.050	-0.000	0.001
		(56.38)	(1.06)	(-0.05)	(-0.09)	(0.16)
R-squared		0.222	0.664	0.513	0.721	0.452
No. of observation		1351	1351	1351	1351	1351
No. of plots		398	398	398	398	398
No. of households		281	281	281	281	281
Equality of coefficients test F-statistics [1]						
(a)=(b)		0.26[0.61]	3.26[0.07]	11.43[0.00]	13.90[0.00]	1.52[0.22]
(b)=(c)		0.37[0.54]	0.94[0.33]	0.04[0.84]	0.03[0.87]	0.25[0.62]
(a)=(c)		0.01[0.91]	1.61[0.20]	24.66[0.00]	13.69[0.00]	0.32[0.57]

Note: *P*-values in brackets. MSRI plot dummy=1 if the plot is used to cultivate MSRI rice at the time of the MSRI training and thereafter. Base year is 2010. Inverse probability weights included to account for attrition. For columns (6) to (10), only farmers with both MSRI and non-SRI plots are included.

t-statistics in parenthesis. ***p<0.01, **p<0.05, *p<0.1.

Table 4. Estimated Plot-Level Impact of MSRI (Average Treatment Effect by Kernel and Bias-Corrected Nearest Neighbor Matching)

		Kernel matching[1)]					Nearest neighbor matching (bias-corrected)[2)]	
		MSRI plot	Non-SRI plot	ATT	s.e.	Rosenbaum bounds critical level of odds ratio[3)]	ATT	s.e.
Paddy yield	(tons/ha)	5.09	2.71	2.38***	0.25	7.7	2.17***	0.24
Value of production	(USD/ha)	1069.4	640.2	429.2***	59.4	5.4	421.9***	51.0
Rice income	(USD/ha)	693.6	316.0	311.7***	64.7	3.6	353.5***	62.0
Rice profit	(USD/ha)	318.4	52.6	265.8***	59.9	2.4	245.3***	61.4
Total cost	(USD/ha)	751.0	587.6	163.4***	44.1	2.4	176.6***	50.9
Labor cost	(USD/ha)	524.0	381.1	142.9***	38.2	1.9	99.4*	52.5
Hired labor cost	(USD/ha)	177.5	191.3	-13.8	30.2	-	-54.7	40.2
Family labor cost	(USD/ha)	346.5	189.9	156.7***	34.3	2.2	177.1***	27.4
Machine/animal cost	(USD/ha)	92.5	110.2	-17.7	10.4	-	-20.0	12.8
Input cost	(USD/ha)	116.0	61.8	54.2***	11.9	2.3	63.8***	11.8

Note: The exchange rate used is USD 1 = TZS 1,583 (year 2013).

*** p<0.01, **p<0.05, *p<0.1.

We use an Epanechnikov kernel matching with bandwidth of 0.06 and obtain standard errors by bootstrapping with 500 replications.

We use one-to-two matches with robust standard errors.

We report the value of odds ratio of MSRI use, which alters the results of our statistical inference at the 10% level based on Rosenbaum (2002).

Total cost includes labor cost, machinery or animal cost, and input cost, as well as milling and marketing cost.

Table 5. Sub-Sample Analysis of the Impact of MSRI-Training on Rice Performance (2013) (Household Fixed Effect)

VARIABLES	Paddy yield (tons/ha)	Value of production (USD/ha)	Rice income (USD/ha)	Rice profit (USD/ha)	Total cost (USD/ha)	Labor cost (USD/ha)	Hired labor cost (USD/ha)	Family labor cost (USD/ha)	Machine/animal cost (USD/ha)	Input cost (USD/ha)
=1 if MSRI plot x trainee in 2012 (a)	2.415***	577.145***	533.243***	393.367***	183.778	56.657	-121.908	178.565***	12.959	58.593***
	(4.70)	(5.19)	(3.76)	(2.70)	(1.65)	(0.54)	(-1.34)	(3.02)	(0.57)	(3.67)
=1 if MSRI plot x trainee in 2013 (b)	2.631***	494.194***	448.938***	286.277***	207.917***	187.413***	-39.024	226.436***	-17.464	41.067***
	(8.87)	(7.70)	(5.48)	(3.41)	(3.24)	(3.08)	(-0.74)	(6.63)	(-1.33)	(4.46)
Constant	2.932***	658.664***	340.907***	86.853*	571.810***	408.582***	244.719***	163.864***	102.245***	53.979***
	(16.14)	(16.76)	(6.79)	(1.69)	(14.55)	(10.98)	(7.62)	(7.83)	(12.73)	(9.58)
R-squared	0.614	0.538	0.373	0.204	0.152	0.147	0.031	0.417	0.028	0.31
No. of plots	152	152	152	152	152	152	152	152	152	152
No. of households	76	76	76	76	76	76	76	76	76	76
Equality of coefficients test F-statistics[1]										
(a)=(b)	0.13[0.72]	0.42[0.52]	0.26[0.61]	0.41[0.52]	0.04[0.85]	1.16[0.28]	0.62[0.43]	0.49[0.48]	1.34 [0.29]	0.91[0.34]

Note: This analysis uses the observation of plots cultivated by 74 trainees (among 110 trainees) for whom we have both MSRI plots and non-SRI plots data.

Total cost includes labor cost, machinery or animal cost, and input cost, as well as milling and marketing cost.

Appendix Table 1. First-Stage Estimation on the Determinants of MSRI-Rice Plot in 2013

VARIABLES	Probability of MSRI rice plot	(for ref) Probability of MSRI training
Plot characteristics		
Slope is steep (=1)	-0.884*	
	(-1.86)	
Log of walking time from home to plot (hrs)	-0.049	-0.093
	(-1.02)	(-1.34)
Household characteristics		
Head is farmer (=1)	0.793*	0.950**
	(1.95)	(2.12)
Age of household head	0.045	0.041
	(0.85)	(0.68)
Age of household head squared	-0.000	-0.000
	(-0.88)	(-0.66)
=1 if female-headed household	-0.541*	-0.718**
	(-1.84)	(-2.14)
Average years of schooling of adult members	0.128**	0.101*
	(2.44)	(1.73)
Log of number of working adults (age between 15 and 65)	-0.412*	-0.550*
	(-1.64)	(-1.78)
Ratio of dependents to working adults	0.019	-0.068
	(0.12)	(-0.35)
Log of cultivating rice plots per working adult	-0.029	-0.000
	(-1.36)	(-0.02)
Log of household assets	0.036	0.055
	(0.53)	(0.72)
Existence of relationship with sub-village leaders	-0.071	0.314
	(-0.33)	(1.15)
Log of walking time from home to meeting place (hrs)	0.183***	0.275***
	(2.68)	(3.34)
Constant	-2.907*	-2.367
	(-1.90)	(-1.35)
Village dummies	Included	Included
No. of plots	315	
No. of households	210	210

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 2. Balancing Test on Covariates (Kernel Matching at the Plot Level)

VARIABLES	Pre-match	Post-match
t-value on the difference in means		
Slope is steep (=1)	-1.36	0.31
Head is farmer (=1)	1.36	-0.26
Age of household head	-0.15	-0.05
Age of household head squared	-0.15	0.09
=1 if female-headed household	-0.98	0.19
Average years of schooling of adults members	1.09	-0.22
Log of number of working adults (age between 15 and 65)	-0.62	-0.50
Proportion of dependents to working adults	0.12	0.18
Log of cultivating rice plots per working adult	-0.41	-0.22
Log of household assets	0.92	-0.24
Log of walking time from home to plot (hrs)	-0.47	-0.17
Existence of relationship to sub-village leaders	0.55	0.13
Log of walking time from home to meeting place (hrs)	2.37**	0.27
Pseudo R2	0.05	0.00
p-value of LR	0.07	1.00
Median absolute bias	7.4	1.6

*** p<0.01, ** p<0.05, * p<0.1.

Note: The t-test results show the statistically significant differences in the characteristics of the plots/households before the matching was removed and after the matching, thus indicating the matching procedure is successful.

The p-value of LR shows the result of the test of the joint insignificance of all the regressors.

[1] The main components of SRI include (1) early transplanting of seedling that is 8–12 days old, (2) shallow planting (1–2 cm) of one or two seedlings per hill, (3) sparse planting in a square grid (more than 20×20 cm), and (4) intermittent irrigation (Moser and Barrett 2006; Stoop, Uphoff and Kassam 2002; Takahashi and Barrett 2014).

[2] Out of these 10 villages, KPL occupies the land in Mkangawaro, Lukolongo, and Mngeta villages.

[3] We planned to interview 40 participants and non-participants in each village. The reduction of sample size is caused by the absence of the farmers in the list on the interview date.

[4] We confirmed that the main results of our analyses remain unchanged even when we use the balanced panel data by omitting those households who did not cultivate rice in any single year within the 4 years under study.

[5] In 57 sample plots, farmers split one plot (let it be plot A) into two and adopt MSRI technologies in one plot (plot A') but not in the other (A'') after they attend MSRI training. In this case, we consider the plots A' and A'' as two different plots. We use the information for plot A as yield and technology adoption in pre-training years for both plots A' and A'' when we construct panel data.

[6] For the robustness check, we estimate the model by using household fixed effect to control household-specific characteristics (x_{vi}), which may include farmers' innate ability or motivation. We also estimate the model without controlling for any fixed effect to examine the spill-over effect from trainees to non-trainees in training villages or non-training villages. The main result does not change. The estimated results are available for readers upon request.

[7] We also conduct balancing tests on the differences in means as shown in appendix table 2. We find that no covariates are significantly different between MSRI plots and non-SRI plots after matching, suggesting that our matching procedure is successful in generating relevant comparison groups (Takahashi and Barrett 2014).

[8] As farmers become more familiar with MSRI technologies over time, they may be able to monitor hired labor more effectively, so that family labor may be substituted for by hired labor to a greater extent in the future.