Climate change perception and system of rice intensification (SRI) in Tanzania: A moment approximation approach*

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Abstract

This article assesses the impact of the adoption of the system of rice intensification (SRI) on the first three moments of rice yields and household income in Tanzania, using household and farm level data together with climate change perception. Using an endogenous switching regressions model, we find that climate change perception determines SRI adoption, and impacts primarily the moments of income. Furthermore, the large and positive average effect of SRI on income variability, is not compensated for by the increase in skewness (reduction in downside risk), which may explain why SRI adoption rates remain low in Tanzania.

Key words: SRI adoption; risk, climate change perception; moment approximation, variance, skewness; Tanzania

JEL Classification: Q16; Q18

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1 Introduction

The growing literature on climate change predicts that Africa's agrarian economies are likely to disproportionately bear the burden of increased temperature and erratic precipitation through substantial agricultural yield losses (Dinar, et al., 2012; Solomon et al., 2007; Kurukulasuriya et al., 2006). Climate change is indeed likely to exacerbate underlying risks associated with climate-dependent economic activities such as rainfed agriculture, and to reduce investment under such a risky environment (Adger et al., 2003; Moser and Barrett, 2003; Christiaensen and Demery, 2007; Alem et al., 2010). Adaptation strategies are therefore essential to mitigate the adverse consequences of changing climatic conditions. In this context, technologies that raise farmers' crop productivity while improving yield stability are particularly valuable. For instance, many conventional technologies, such as those that accompanied the Green Revolution (e.g., improved varieties adoption) often result in greater crop yield, but at the expense of increased yield variability and income risk. As Antle and Crissman (1990) demonstrate in a case study of rice production in the Philippines, individual conventional technologies do exhibit risk-enhancing features, although appropriate combinations of management and inputs may achieve lower production risk. In this paper, we assess the impact of an unconventional technology, the System of Rice Intensification (SRI), on mean agricultural yield and household income, as well as on their variability and exposure to downside risk, captured by the variance and skewness, respectively.

The system of rice intensification (SRI) was developed in the 1980s in Madagascar as a set of alternative management practices to help poor farmers-who were typically excluded from the input-intensive Green Revolution-to increase yields, while using cheap organic inputs and reducing water use. Most African farmers struggle to access sufficient water resources due to insufficient rainfall. They also do not have access to irrigation technologies, improved seeds, and inorganic fertilizers due to their cost. . , SRI seems therefore to be the perfect climate change adaptation strategy for these farmers. SRI is based on four principles that rely on an unconventional set of agronomic practices. Unlike traditional paddy rice cultivation, SRI does not rely on flooding, but rather on moist soil, with intermittent irrigations (Stoop, 2002), which is particularly suited to regions where water is a limiting factor. Its guiding principles are: (1) early transplanting (eight to 15 days old) of carefully managed seedlings; (3) single, widely spaced transplants to allow early and regular mechanized weeding; (3) careful and controlled water management; and (4) application of compost to the extent possible (de Laulanié, 1993a, 1993b; Stoop, 2002; Noltze et al., 2013). Despite skepticism from the scientific agricultural community, SRI has delivered substantially higher yields, while reducing input requirements (fewer seeds, less water and inorganic fertilizers) than the conventional paddy method (Noltze et al., 2013; and Katambara et al., 2013a). Furthermore, SRI is reported to produce more robust and resilient crops in the face of extreme weather events, pests, and disease

(Stoop, 2002; Noltze et al., 2013). As a result, SRI has diffused over the past two decades in the paddy rice growing regions in Asia (e.g., China, India, Vietnam) as well as in Africa.[1] It is believed that these outstanding outcomes will help poor and vulnerable farmers to increase their yields and incomes, while making them resilient to the vagaries of unfavorable weather, especially in Africa. However, the spatial diffusion of SRI, and the slow adoption rate and high rate of disadoption (abandonment) among poor farmers has been puzzling (Rakotomalala, 1997; Stoop, 2002; Moser and Barrett, 2003, 2006; Takahashi and Barrett, 2013).

Why would resource-poor rice growers not adopt a method that promises to relax the binding constraints they face under the conventional paddy method? Various explanations have been offered. Moser and Barrett (2003, 2006) attribute the slow adoption and non-trivial disadoption rates to the large hidden opportunity costs of engaging in SRI. Because SRI is a labour-intensive cultivation method, it typically requires a reallocation of paid off-farm labour into unpaid family farm labour to perform time-consuming tasks such as weeding and compost preparation.[2] Abdulai and Huffman (2014) echo this argument in their analysis of low adoption rates of soil and water conservation technologies in rice growing regions of Ghana. For some poor farmers who have very few opportunities to earn cash, the cost is simply too high.[3] Besides, since SRI constitutes a set of new, unconventional, and unfamiliar agronomic practices, success relies heavily on sustained training and extension services. When these services are unavailable, or not sustained over time, farmers may have little incentive to adopt SRI. Yet another explanation is that SRI may have impacts beyond the mere average yields and average income. If SRI were to have an impact on the variability of yields and income, or on the risk of lower yields and lower income, then these impacts could also explain this puzzle. Indeed, farmers who are averse to increased variability (risk averse) or averse to increased exposure to downside risk, would abstain from adopting SRI, despite its potential to deliver higher mean yields and mean income.

In this paper, we explore this third and complementary avenue to understand the puzzlingly low adoption of SRI. Our empirical strategy relies on an endogenous switching regression model that estimates jointly the selection into SRI, as well as the effect of SRI on the first three moments of yields and income.That is, on expected rice yield and income, but also on their variability and exposure to downside risk. This study extends the limited literature on the variance and downside risk effects of technology adoption by focusing on the System of Rice Intensification (SRI), an integrated technology designed to reduce production risks. By doing so, we move away from the narrowly focused analysis of productivity impacts. For this purpose, a moment-based approach will be developed that will characterize the stochastic nature of the technology (Kim and Chavas, 2003; di Falco and Chavas, 2009; di Falco and Veronesi 2014).

Our analysis highlights the importance of farmers' climate perception, both on the adoption decision and on the moments of yield and income. Studying income risk in the context of climate variability is critical because, in the presence of low adaptive capacity, risk exposure can be heavily exacerbated by unfavourable climatic conditions (Pecetti et al., 1992; Loss and Siddique, 1994; Di Falco and Chavas, 2009). In addition to underlying risk considerations, the responsiveness of income risk would therefore depend on climate change and its perceptions.

Analysis of climate change perceptions and its impact on farm level decision making, while recent, is a fast growing area of research. Madison (2007) and Bryan et al. (2009) assess the ability of farmers in Africa to detect climate change, and attempt to ascertain how farmers adapt to whatever climate change they believe occurred. Their findings show that farmer behavioural responses to perceived climate change tend to be related more to recent climate events or trends rather than to long-term changes in average conditions (Smit et al., 2000; Thomas et al., 2007; Bryan et al., 2009). In addition, several studies find local knowledge in decision making, as it pertains to climate risk, to bea critical parameter in decision making (Roncoli et al., 2001, 2002; Vogel and O'Brien, 2006; Thomas et al., 2007). Others find that farmers base their decision to adapt their farming practices not only on changes in average conditions, but also on a number of other climate factors observed through personal experience, such as extreme events, rainfall frequency, timing, and intensity, and early or late frosts, highlighting the importance of climatic perceptions (Smithers and Smit, 1997; Roncoli et al., 2002; Vogel and O'Brien, 2006; Thomas et al., 2007).[4]

The rest of the paper is organized as follows: In section 2, we present background on SRI adoption and climate change in Tanzania. The survey strategy and data are discussed in section 3, while the estimation methodology is provided in section 4. Section 5 presents the empirical findings and section 6 concludes the paper.

2 Background: Climate change and SRI adoption in Tanzania

Vulnerability of rainfed agriculture to climate change could have devastating consequences for the welfare of smallholder farmers in Tanzania, due to reduced agricultural yields. Recent findings suggest that climate change may yield shorter growing seasons and stress on cash crops due to increased moisture, heat, insects, and pests (Mongi, et al., 2010), resulting in likely deteriorations in food security (Arndt et al., 2011). In this regard, Rowhani et al. (2011) show that a 2°C-rise in temperature by 2050 could induce a decline in mean yields of maize, sorghum, and rice by 12%, 8.8% and 7.6%, respectively.

The impact of climate change on Tanzanian agriculture will not only be influenced by mean changes in climatic conditions, but also by the associated variability. For instance, Rowhani et al. (2011) argue that ignoring climate variability underestimates the decline in maize, sorghum, and rice yields by 3.6%, 8.9%, and 28.6%, respectively. Moreover, Ahmed et al. (2012) find high yield variability of staple grains to be associated with large increases in poverty. However, in analyzing the economy-wide effects of climate change in Tanzania, Bezabih et al. (2011) contend that, despite the projected reduction in agricultural productivity, the negative impacts could be fairly limited, provided policies are implemented that enable farmers to respond appropriately to changes in climatic conditions.

Policies promoting adoption of technologies that contribute to farmers' adaptation to climate change and climate variability are of particular interest in this regard. However, in addition to their costliness, conventional yield-enhancing technologies (e.g., improved varieties, cultivation of paddy rice) may be unsuitable for poor and vulnerable farmers whenever they lead to a rise in yield variability and to greater exposure to downside risk (Kim and Chavas, 2003), especially in a context of changing climatic conditions. For instance, in Tanzania, the conventional flooding techniques in paddy fields are deemed inefficient, given limited water availability and growing seasonal variability (Katambara et al., 2013a). The recent introduction of the System of Rice Intensification (SRI) in 2006 aims to lessen the water intensity of rice production, improve low yields, and consequently increase farmers' incomes. Crops cultivated under SRI are also reported to be more resilient in the face of extreme weather events, pests, and diseases. This novel and unconventional approach seems particularly suited to poor farmers in water scarce regions because it requires reduced inputs (fewer seeds, less waterand less inorganic fertilizers are needed). A simplified variant of the SRI developed in Madagascar was introduced in several regions of Tanzania in 2006. It entails shallow planting of 1-2 cm of transplanted seedlings aged 8 to 12 days on a square grid of 20-25 cm with intermittent irrigation, fertilizer application and weeding (Nakano et al., 2014; Africare, 2010; Katambara et al., 2013b). The SRI has met some success with regard to yield improvement, water efficiency, productive tillers and panicles requirements of rice production (Katambara et al., 2013a). For example, in Mkindo (Morogoro Province) water efficiency improved by up to 64%, while yields increased from 3.8 tons/ha (with conventional methods) to 6.3 tons/ha using SRI (Katambara et al., 2013a). In addition, fewer and more widely spaced transplanted seedlings (up to 10 kg/ha fewer seeds)decreased disease vulnerability and enhanced wind resiliency due to healthier and more robust plant stems, and lower soil erosion (Katambara et al., 2013a). Despite these seemingly promising results, adoption of SRI has been limited in Tanzania (Katambara et al., 2013a). In the following sections, we investigate the determinants of SRI adoption in the Morogoro region of Tanzania, as well as the effect of adoption on the first three moments (mean, variance, and skewness) of agricultural yield and farmer's income.

3 Data

The data used for the empirical analysis is based on a survey in the Kilombero district of Morogoro region, one of the largest rice producing regions in the country. In this district, 334 rice farming households are randomly selected from eight villages for the farming season ending in June, 2013. In the Tanzanian setting, an SRI package consists of seed sorting prior to planting, square grid planting, use of saro seed varieties, and application of chemical fertilizers. We consider a household to be a SRI adopter if it applies at least three of the four components. However, none of these components is applied universally by all adopting households, which underscores the fact that SRI adoption is partial.[5]

The choice of plots that were allotted to SRI occurred as follows. Initially, farmers gave information on all of their rice-planted plots in the survey year, by SRI status. It was noted that multiple plot cultivation was only common with traditionally farmed varieties but not with SRI. Whenever a household adopted SRI the method is only applied in one of its plots. This explains our choice of only one plot for the SRI. For the non-SRI plots, a representative plot is selected using a simple random technique in order to minimize plot-level selection bias. In Section 4, we discuss the econometric steps we take to further control for potential selection bias resulting from systematic selection of plots into SRI and non-SRI categories.

With an adoption rate of approximately 60%, a total of 193 households adopted SRI on one of their plots during the previous agricultural season. The survey includes detailed socio-economic household characteristics, plot-specific information, as well as farming inputs used (from plot preparation to the post-harvest), alongside output and marketing information. Table 1 below presents the mean of the variables used in the regressions by SRI adoption status, as well as the mean difference between the adopter and non-adopter groups.

On average, households adopting SRI tend to be larger, headed by older farmers (44.5 versus 41 years for non-adopters) and have more males of working age (i.e., 15 years and above). They are typically wealthier, have more experience in rice farming, and a denser social network. They also tend to receive visits from extension services. These differences are statistically significant at least at the 5 percent level. However, we do not find any statistically significant difference across the two groups regarding their level of education and marital status.

Farmers typically practice SRI on smaller plots (1 acre compared to 2.8 acres) that are located closer to their homesteads (3.7 km vs. 4.7 km). On average, these plots are more fertile than the conventionally cultivated plots. However, we do not find any significant difference across plots on other observable characteristics, such as slope and soil type.

Consistent with previous literature, practising SRI is shown to require considerably more labour. On average, an SRI plot requires almost twice as much labour supply (64 man-days vs. 33 man-days for non-SRI plots). This substantial difference emphasizes the need for evaluating the impact of the technology beyond mere agricultural yield, given both the direct and indirect costs of such extra labour requirements. In addition, given the potential reallocation of labour by SRI farmers from other income generating activities to SRI plots, assessing the higher moments impact of the technology becomes even more important, since the adopting household in this case has less opportunity to diversify against the risk of bad outcomes.

The key dependent variables, in addition to SRI adoption, are yield, and total household income. Yield is calculated as total harvest per acre of cultivated land in thousands of tonnes. Given the labour intensive nature of SRI, it is important to estimate its impact on total household income, accounting for both direct and indirect costs associated with such extra labour demand. Because the adoption of SRI requires additional labour supply (expressed in man-days), increased labour costs could negatively affect both farm and off-farm incomes. Total household income constitutes both total farm profit and off-farm earnings from all sources, including remittances within the same agricultural season. Farm income is calculated as difference between total revenue and total production cost per acre, multiplied by total size of the cultivated plot. While revenue is computed as the product of the farm gate price of paddy per kilogram and production, we calculate total cost as the sum of all input costs (including seeds, labour, herbicides, and fertilizer) used during the entire farming year, starting from plot preparation to the harvest period. It should be noted that labour costs comprise both household labour (computed using the shadow wage approach of Jacoby, 1993) and cost for hired labour. Preliminary assessment suggests that SRI farmers obtain significantly more yield and total household income than their counterparts. On average, SRI farmers harvest 7.51 in log kg per acre and earn a total income of TZS 1.6 million, compared to a yield of 6.85 (log kg per acre) and an income of TZS 1.2 million for non-adopters.

Finally, households are also asked about their perceptions regarding changing climatic patterns—average annual rainfall and temperature—over the past 10 years. Perception about climate change is captured by two dummy variables that indicate whether a farmer has noticed a pattern of rising average temperatures or declining rainfalls over the past decade. These dummy variables are constructed based on farmers' direct responses. Most farmers have perceived such changing patterns. Nearly 60% of SRI adopters have observed a decrease in the average rainfall, as opposed to 53% of the non-adopters, although the difference is not statistically significant. In addition, approximately 64% of both SRI adopters and non-adopters believe that average annual temperatures are increasing.

It is, however, important to note that, due to the problem of self-selection (or endogeneity bias) we cannot attribute all the differences presented in Table 1 to SRI adoption. Given that SRI farmers are more socially connected, receive more extension services, and apply the technology on more fertile plots, adopters and non-adopters could still have outcome differences even without technology adoption.

4 Conceptual framework and econometric methodology

The premise of our analysis is that farmers are expected to grow yield-enhancing varieties such that welfare is improved from the gains of higher yields and profit. Further, to the extent that SRI is perceived and conceived as a risk mitigating practice, it is expected to have additional welfare benefits to poor and risk-averse farmers (Kim and Chavas, 2003). Our analysis relies on a moment-based specification of the stochastic production function (Antle 1983; Antle and Goodger 1984). The method has been widely used in the context of risk management in agriculture (Just and Pope 1979; Kim and Chavas, 2003; Koundouri et al. 2006; and Di Falco and Chavas, 2009). It is based on Pratt's (1964) concept of risk premium as a measure of the cost of private risk bearing, where technological progress may be either risk-increasing or risk-decreasing, depending on whether it increases or decreases the relative risk premium. As a result, the welfare of risk averse farmers may be adversely affected by mean-preserving increases in the variance of yield (or income), and in the associated skewness (e.g. the probability of crop failure). Since increased variance does not distinguish between unexpectedly good and bad events, and since the avoidance of crop failure is a major objective of farmers in Sub-Saharan Africa (Di Falco and Chavas, 2009), the notion of skewness is particularly important. While risk averse farmers may have an incentive to reduce the variance of returns, farmers exhibiting aversion to downside risk have an incentive to grow varieties that positively affect the skewness of the distribution of returns, thus reducing their exposure to downside risk (e.g. severe drought leading to crop failure) (Kim and Chavas, 2003; Di Falco and Chavas, 2009). Thus, a moment-based approach is able to capture the full extent of risk exposure.

We therefore estimate the impact of the new technology (SRI) on outcome variables between adopters and non-adopters beyond the usual mean difference, to also assess its impact on higher moments of the outcome variables (i.e. variance and skewness). Our empirical approach addresses two estimation considerations. First, there is a potential problem of simultaneity bias because, although adoption of SRI may result in enhanced yields and incomes, it may also be the case that higher yields and incomes increase the probability of adopting SRI. Second, some observed and unobserved characteristics (household or farm characteristics), may concurrently affect both selection (adoption of SRI) and outcome (income or yield). Estimation of the effects of adoption via ordinary least squares (OLS), which assumes random selection, is therefore potentially biased.

Standard treatment effects models typically include a treatment dummy as an explanatory variable, assuming that the impact on the outcome variable can be represented as a simple intercept shift. Noltze et al. (2013) argue that this is inappropriate because farm and farmer conditions may systematically influence SRI impacts on yields and household incomes. Following previous studies (e.g., Di Falco et al., 2011; Noltze et al., 2013; and Abdulai and Huffman, 2014), we employ an endogenous switching regression model (ESR) to address this estimation bias. Apart from its ability to correct for selection bias due to observable and unobservable differences between groups, ESR enables us to estimate the average treatment effect on both the treated (ATT) and the untreated households (ATU). The endogenous switching regression model consists of two stages. The first stage is a selection equation that is based on a dichotomous choice function (probability of adopting SRI). The second stage is the outcome equations, and features the determinants of the outcome equations (yield or income) for both adopters and non-adopters.

In the first stage, given observed and unobserved characteristics, each farmer elects to adopt the new SRI technology whenever their latent (unobserved) expected benefits from adoption (SRI^*) are positive, and abstains otherwise. The decision to adopt is, however, observed, and is captured by the dummy variable SRI, which takes a value 1 in the case of adoption and a value of 0 in the case of non-adoption. The first stage selection equation is typically modeled as follows:

$$
\begin{aligned}
SRI_i^* &= S_i'\gamma + \upsilon_i \\
SRI_i &= \begin{cases} 0 & \text{if } SRI_i^* \leq 0 \\ 1 & \text{if } SRI_i^* > 0 \end{cases}
\end{aligned}
$$

where S_i is a vector of exogenous variables affecting the probability of adopting SRI. These variables include (*i*) households' characteristics such as education, age, marriage status, experience, and wealth; (*ii*) farm characteristics such as farm size, fertility of the soil, and slope of the terrain; (*iii*) social network and training; and (*iv*) perception about changing climatic patterns, which is a novelty in the SRI literature (see for example Takahashi and Barrett, 2013; Noltze et al., 2013).

The second stage outcome equations are explicitly modeled differently according to the farmers' adoption decision. The model accommodates the two adoption regimes:

$$
\begin{aligned}
\text{Regime 0: } y_{0i} &= X_i'\beta_0 + \varepsilon_{0i} \text{ if } SRI_i = 0 \\
\text{Regime 1: } y_{1i} &= X_i'\beta_1 + \varepsilon_{1i} \text{ if } SRI_i = 1
\end{aligned}
$$

where y_{0i} and y_{1i} denote the values of the outcome (mean, variance and skewness of yield and income) for farm household i in each adoption regime; X_i is a vector of exogenous covariates that influences the outcome in each regime; and β_0 and β_1 are the associated vectors of coefficients. This method allows for correlation between the three error terms ε_{0i}, ε_{1i} and υ_i —which are assumed to be jointly normally distributed $\mathcal{N}(0,\Sigma)$ where the covariance matrix is written as:

$$\Sigma = \begin{bmatrix} \sigma_\upsilon^2 = 1 & \sigma_{0\upsilon} & \sigma_{1\upsilon} \\ \sigma_{0\upsilon} & \sigma_0^2 & . \\ \sigma_{1\upsilon} & . & \sigma_1^2 \end{bmatrix}.$$

The covariance terms between ε_{0i} and ε_{1i} are not defined (.) since a given farmer cannot be simultaneously an adopter and a non-adopter. The first variance σ_υ^2 is normalized to one to ensure statistical identification of parameters.

We typically estimate this endogenous switching regression model by using a consistent and efficient procedure that relies on full information maximum likelihood (FIML) with observation $i's$ likelihood written as follows:

$$\begin{aligned}
\mathcal{L}_i &= \Pr\left(y_i \,\text{and}\, SRI_i = \{0,1\}\right) \\
&= \left[\Pr\left(y_i = y_{1i}, SRI_i = 1\right)\right]^{SRI_i} . \left[\Pr\left(y_i = y_{0i}, SRI_i = 0\right)\right]^{1-SRI_i} \\
&= \left[\Pr\left(y_i = y_{1i}\right)\Pr\left(SRI_i = 1 \middle| y_i = y_{1i}\right)\right]^{SRI_i} . \left[\Pr\left(y_i = y_{0i}\right)\Pr\left(SRI_i = 0 \middle| y_i = y_{0i}\right)\right]^{1-SRI_i}
\end{aligned}$$

where

$$\Pr\left(y_i = y_{ji}\right) = \Pr\left(y_i = X_i'\beta_j + \varepsilon_{ji}\right) = \frac{1}{\sigma_j}\phi\left(\frac{y_i - X_i'\beta_j}{\sigma_j}\right)$$

$$\Pr\left(SRI_i = 1 \middle| y_i = y_{ji}\right) = \Pr\left(\upsilon_i \middle| \varepsilon_{ji} = \varepsilon_{j0} > -S_i'\gamma\right) = \Phi\left(\frac{S_i'\gamma + \rho_{j\upsilon}\left(y_i - X_i'\beta_j\right)/\sigma_j}{\sqrt{1-\rho_{j\upsilon}^2}}\right)$$

$$\Pr\left(SRI_i = 0 \middle| y_i = y_{ji}\right) = \Pr\left(\upsilon_i \middle| \varepsilon_{ji} = \varepsilon_{j0} \leq -S_i'\gamma\right) = 1 - \Phi\left(\frac{S_i'\gamma + \rho_{j\upsilon}\left(y_i - X_i'\beta_j\right)/\sigma_j}{\sqrt{1-\rho_{j\upsilon}^2}}\right)$$

where ϕ and Φ are the standard normal probability density and cumulative distribution functions; and $j = 0, 1$ represent SRI adaptation and non-adaptation, respectively.

For proper identification of the selection equation coefficients, we assume at least one element of the vector of covariates S in the SRI equation is excluded from the outcome equations. Our *exclusion restriction* relies on two sets of variables. First, we rely on variables relating to social network (density of the connection and number of years in the village) which, as we will see, do not affect the outcome directly but through SRI adoption decision. Secondly, as another excluded variable, we include a variable that captures a management practice that is closely associated with SRI. For instance, the practice of sorting seeds is particularly advocated within SRI. We can presumably assume that this activity will affect yield or income (mean, variance, and skewness) only through SRI rather than directly. The admissibility of the instruments is tested by performing the falsification test introduced by di Falco et al. (2011). That is, a valid set of instruments will affect the decision to adopt SRI but not the moments of yield or income for non-adopters. As we show in Panel C of Tables 2 and 3, based on the admissibility tests, we can never reject the null that the chosen instruments are valid.

As noted before, following Kim and Chavas (2003), we estimate our switching models (for total harvest and total income), considering not only the mean levels as dependent variables, but also the variance, to capture variability, and the skewness, to capture exposure to downside risk. Considering the variance and its skewness in addition to its levels allows us to identify potential trade-offs between productivity gains and income stability (the risk of income loss/crop failure). For example, if we consider regime 1, the second and third moments (variance and skewness) are calculated as:

$$\begin{aligned} \text{Variance} &= \mu_{2y_1} = \mathbb{E}\left[(y_1 - \mathbb{E}(y_1))^2\right] \\ \text{Skewness} &= \mu_{3y_1} = \mathbb{E}\left[(y_1 - \mathbb{E}(y_1))^3\right] \end{aligned}$$

To compare differences in total yield and total income between adopter and non-adopter households, we calculate treatment effects using estimates from the switching regression models. Two effects are of particular interest. First, we estimate the effect of treatment on adopters or treated (i.e., ATT), that is, the effect of adoption on adopters. Secondly, we estimate the effect of treatment on non-adopters or untreated (i.e., ATU), that is, the effect of adoption on non-adopters had they adopted SRI. The unbiased treatment effects ATT and ATU that control for observed and unobserved heterogeneity are given by:

$$ATT = \mathbb{E}(y_{1i} \mid SRI_i = 1) - \mathbb{E}(y_{0i} \mid SRI_i = 1)$$

$$ATU = \mathbb{E}(y_{1i} \mid SRI_i = 0) - \mathbb{E}(y_{0i} \mid SRI_i = 0)$$

where

$$\begin{aligned} \mathbb{E}(y_{1i} \mid SRI_i = 1) &= X_i'\beta_1 + \lambda_1\sigma_{1v} \\ \mathbb{E}(y_{0i} \mid SRI_i = 1) &= X_i'\beta_0 + \lambda_1\sigma_{v0} \\ \mathbb{E}(y_{1i} \mid SRI_i = 0) &= X_i'\beta_1 + \lambda_0\sigma_{v0} \\ \mathbb{E}(y_{0i} \mid SRI_i = 0) &= X_i'\beta_0 + \lambda_0\sigma_{1v} \end{aligned}$$

The inverse mills ratios λ_0 and λ_1 evaluated at $S_i'\gamma$ characterize the truncated error terms so that:

$$\begin{aligned}\mathbb{E}\left(\varepsilon_{1i} \mid \upsilon_i > -S_i'\gamma\right) &= \frac{\phi\left(S_i'\gamma\right)}{\Phi\left(S_i'\gamma\right)}\sigma_{1\upsilon} = \lambda_1\sigma_{1\upsilon} \\ \mathbb{E}\left(\varepsilon_{0i} \mid \upsilon_i \leq -S_i'\gamma\right) &= \frac{\phi\left(S_i'\gamma\right)}{1-\Phi\left(S_i'\gamma\right)}\sigma_{0\upsilon} = \lambda_0\sigma_{0\upsilon}\end{aligned}$$

5 Results and discussion

We estimate the impact of SRI on the first three moments of yield and total household income (i.e., mean, variance, and skewness) using endogenous switching regression models. We report the two stages of our model in Table 2 and Table 3. The choice of variables in the estimation draws from the theoretical and empirical variables in Di Falco and Chavas (2009). We first discuss the correlates of SRI adoption, and, second, we examine the determinants of the mean, variance, and skewness for both yield and income.

5.1 Determinants of SRI adoption

Our first step is to shed some light on the observed factors that characterize SRI adopters. We find that wealthier households, and those who rely on agriculture as their main source of income are more likely to adopt SRI. The fact that SRI attracts wealthier farmers is somewhat unexpected, given that this unconventional practice was initially designed to enable *poorer* farmers to enhance their yields and reduce water consumption. This unexpected pattern in Tanzania is also captured by the fact that farmers using more chemical fertilizers are more willing to adopt this new practice. By contrast, SRI was introduced in Madagascar for farmers who typically could not afford expensive chemical fertilizers and were rather relying on manure and other organic fertilizers. As expected, greater labour supply is a determining factor, since SRI is more labour-intensive (extra labour is particularly needed for weeding and seed sorting) than conventional paddy rice farming. Similarly, seed sorting is also associated with SRI adoption. Farmers owning farmland of smaller size, greater soil fertility, and located within close proximity are more eager to adopt SRI. A possible explanation is that, given the recent introduction of SRI, farmers are still experimenting before considering a scale up of this practice. An alternative explanation could be that farmers are simply diversifying their portfolio of technology. It is also possible that, like in other settings and regions (e.g., Madagascar), farmers have dedicated only relatively small plots to SRI, despite its benefits because of the high opportunity costs associated with this practice (Moser and Barrett, 2003).

Both formal education (i.e., years of schooling) and extension services-based training influence the adoption decision positively, albeit the former tends overall to be statistically less significant. The fact that farmers who receive visits from extension agents are more likely to adopt SRI could be because of the complex and un-conventional nature of SRI. In addition, greater social connection (as measured by the number of social groups of the farmer, and the number of years they have been in the village), is associated with technology adoption.

Importantly, we find that changing climatic patterns (as perceived by farmers) influence the decision to adopt SRI. Typically, two types of climatic changes have been perceived by sampled farmers: Reduced rainfall and increased temperature. Those who have observed decreasing rainfall patterns are more inclined to adopt SRI than those who have not perceived these changes. This suggests that adoption of SRI could be regarded as an adaptation mechanism to climate change, since one of its key objectives is to reduce water usage in rice farming. On the other hand, perception of long-term increasing temperatures and SRI adoption are negatively associated, although the relationship is statistically significant only for the mean yield.

We find similar results for the variance and skewness of the yield. The only difference is that education and perceived temperature increase are no longer significant. Finally, the first stage of the income models (Panel C of Table 3) show very similar results.

5.2 Switching regression results for mean, variance and skewness of yield and total income

For the average farmer who has adopted SRI (see Panel A of Table 3), the first three moments of income are primarily influenced by labour supply, plot distance from the homestead, and perception of rising temperature. An increase in these variables results in greater mean income and reduced downside income risk. These positive effects are accompanied by enhanced income variability. Surprisingly, households who primarily rely on agriculture experience reduced mean income and increased downside income risk. These adverse effects are however mitigated by the decrease in income variability. It is also noticeable that farmers' experience in rice cultivation reduces income variability, while plot size increases it. However, neither variable has a significant effect on expected income or skewness. The results found for rice yield (Panel A of Table 2) are fairly similar although statistical significance is generally more patchy.

Changing climatic conditions, as perceived by farmers, plays a key role in our analysis. In fact, rising temperatures (as perceived by farmers) have a markedly different effect across the group of adopters and non-adopters. Reduced rainfall however does not exhibit such differences. We find that the effect of a rise in temperature as perceived by adopting farmers is to raise expected income and expected rice yield, at the expense of increased variability. Downside risk is also reduced, although it is statistically significant only for income. By contrast, non-adopting farmers' perception of rising temperatures has no statistically significant effect on any of our dependent variables.

The effect of perceived higher temperature runs entirely through adopting farmers. While farmers are less likely to adopt SRI when they perceive rising temperatures, for those farmers who have indeed adopted SRI, the perception of increasing temperature is associated with greater expected yield and variability but also with greater expected income, increased income variability, and reduced exposure to downside income risk. This overall positive effect of perceived rising temperature is somewhat counter-intuitive, though robust. Indeed, although rice grows linearly in the range of 22–31°C, higher temperature adversely affects growth and productivity (Yoshida, 1981; Krishnan et al., 2011). However, increase in mean temperature or episodes of high temperature during sensitive stages of the crop may adversely affect the growth and yield of rice, especially in tropical regions where temperatures are often above the optimal for growth (28/22°C, i.e., 28°C in daytime and 22°C at night).[6] Given that mean temperatures in the Kilimbero district fluctuate between 20.5°C and 26.6°C in a given year, a rise in temperature would still have positive effect on rice yield.

On the other hand, the perception of reduced precipitation negatively affects the mean yield for SRI adopters, but has no effect on its variance and skewness, nor does it have an impact on the moments of income. For non-adopters however, the perception of reduced precipitation has a negative impact on both expected yield and its skewness, but does not affect the moments of income. In brief, farmers who observe reduced rainfall also experience reduced rice yields irrespective of their adoption decision.

Finally, while we can reject the null hypothesis of independent equations for the mean income, the mean yield, and the skewness of yield, the LR test cannot reject independence for yield variance, income variance, and income skewness. This suggests that the hypothesis of absence of sample selectivity bias may be rejected for the former cases but not for the latter cases.

5.3 Average treatment effects

We now present the average treatment effect of adopting SRI (see Table 4). Panel A shows the average treatment effect on the treated (ATT) for the first three moments of rice yield and total income. Panel B in turn presents the average treatment effect on the untreated (ATU).[7]

First of all, we find that SRI adoption has a positive and statistically significant impact on expected yield and expected income. On average, adopters increase their rice production per acre by 13 percent and total income by 83 percent, compared to non-adopters. The impact is economically large and statistically significant at one percent level.

Secondly, we find that adopting SRI raises income variability relative to non-adopters, but has no impact on the variability of rice yield. Thus, risk-averse farmers would likely abstain from adoption, especially with regard to household income. Higher variance of gains from improved agricultural technologies is also documented as the reason why risk averse farmers are less likely to adopt such technologies (e.g. Yesuf and Bluffston, 2009; Tanaka et al., 2010).

Thirdly, we find that SRI adoption has a positive and statistically significant impact on the skewness of rice yield and total income. The combined effect of increased income variance and skewness suggests that the technology increases income uncertainty, but lowers the probability of household exposure to downside income risks. This could explain why, in contrast to the intended goal of opening new opportunities to address the needs of poorer farmers, wealthier farmers (who are typically assumed to be less susceptible to risk aversion) have been more willing to adopt SRI. On the other hand, a reduction in exposure to downside risk (combined with increased expected rice yield and income) could compensate the income risk (due to high variance) and encourage even risk averse farmers to adopt the technology. However, the countervailing effect of positive income skewness is small relative to the increase in income variance.

Panel B presents the average treatment effects for the untreated (ATU) or equivalently for SRI non-adopters. From a policy perspective, these effects, which broadly accord with the ones discussed above, are highly relevant. Our results show that while non-adopters' expected rice yield and expected income would have increased by 5.5% and 32% respectively had they adopted SRI, the variance of the relevant variables increase by a factor of two and three, respectively. Moreover, downside risk exposure is reduced substantially for rice yield and only marginally for income.

Finally, we note that for those farmers who perceive increased temperatures, average productivity and income gains benefit primarily SRI adopters. Indeed, for SRI adopters, the respective coefficients of perceived temperature increase are positive and significant at the 1% level for income and 5% level for yield, but insignificant for non-adopters.

Overall, the finding that despite increased yield and income, increased income variance is not offset by reduced downside income risk may explain why farmers are reluctant to adopt SRI given existing evidence that most farmers are risk averse (Lin et al., 1974; Binswanger, 1981; Antle, 1987; Saha et al., 1994) and downside risk averse (e.g. Binswanger, 1981; Chavas and Holt, 1996; and Kim and Chavas, 2003).

6 Conclusions

This paper presents an impact evaluation analysis of the recent introduction of the System of Rice Intensification (SRI) in Morogoro (Tanzania), with a focus on exposure to risk and downside risk for rice yield and household income, in addition to mean yield and income. Despite the recentness of the intervention, we find evidence of large economic impacts of SRI adoption. Overall, SRI adoption comes with a trade-off between greater expected yields and expected income on the one hand, and increased income variability on the other hand. We also find that SRI has a considerable impact on reducing downside risk, as indicated by the positive and significant coefficients of yield and income skewness. This suggests that the reluctance of risk averse farmers to adopt SRI due to increased income variability may be mitigated by the increase in skewness. These results are obtained using an endogenous switching regression model that estimates jointly the determinants of SRI adoption and the three moments of rice yield and household income. We provide evidence of the importance of wealth, soil fertility, farm size, extension services, social connection, and climate change perception in shaping the decision to adopt SRI. The measures of climate risk perception (in particular rising temperatures) are associated with increased yields and income as well as their variance and skewness. Decreased rainfall however is correlated with reduced yields and increased exposure to downside risk.

The results of this study improve our understanding of the behavioural and policy factors that can help explain constraints and opportunities in the adoption of new technology. This paper suggests that sufficient awareness of the occurrence of climate change can contribute to reduce downside risk exposure, despite increased variance. This provides useful insights on the linkages between climate change perceptions and the income risk impact of new technology. Given the potential for rural climate information to support adaptation and management of climate risk, there is a need to make climate information more accurate, accessible, and useful for farmers (Roncoli et al., 2002; Ziervogel et al., 2005; Hansen et al., 2007).

One important shortcoming of the analysis is that it is based on a cross sectional survey, and thus many of the time-variant variables are only snapshots. Further unmeasured characteristics that are important determinants of adoption and risk factors confound with the observed covariates and the sign and magnitude of the resulting omitted variables bias is unknown. Future studies with panel data features would enable controlling for the effect of such unobserved effects. Further, follow-up research to assess risk effects of the programme—especially by incorporating objective climate change measures (as opposed to climate change perceptions used in this paper), the channels through which specific programme effects materialise, and how benefits are distributed across adopters (given our finding of significant heterogeneity), would be of great interest.

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Table 1: Summary Statistics

Variables	Entire sample		Sub-samples		
	Mean	Std dev	Mean Adopters	Mean Non-Adopters	Mean Difference
Age	42.96	11.87	44.46	40.91	3.54***
Household size	4.71	1.84	4.91	4.44	0.47**
Married (dummy)	0.86	0.35	0.87	0.85	0.02
Male (dummy)	0.91	0.29	0.89	0.94	-0.05
Men	1.51	0.91	1.56	1.43	0.14
Education (in years)	7.00	1.88	7.04	6.94	0.10
Experience rice (in years)	14.91	9.72	15.65	13.90	1.75
Wealth (log wealth)	12.72	1.25	12.89	12.49	0.41***
Total labor supply (in man days)	50.84	68.83	63.62	33.36	30.26***
Chemical fertilizer usage (dummy)	0.54	0.50	0.86	0.09	0.78***
Plot size (in acre)	1.74	2.33	0.97	2.78	-1.81***
Very fertile	0.41	0.49	0.41	0.40	0.010
Fertile	0.92	0.28	0.95	0.87	0.08**
Slopy plot	0.13	0.34	0.11	0.16	-0.040
Plot distance (in km)	4.10	4.39	3.75	4.58	-0.83*
Distance to market (in km)	87.54	203.19	102.8	66.67	36.11
Agriculture as main activity	0.96	0.19	0.97	0.94	0.030
Yield (in log kg per acre)	7.23	0.83	7.51	6.85	0.66***
Total Income (in million TZS)	1.39	2.00	1.58	1.12	0.45**
Extension (dummy)	0.43	0.50	0.62	0.16	0.45***
Perception Rain decrease (dummy)	0.57	0.50	0.60	0.53	0.060
Perception Temperature increase (dummy)	0.64	0.48	0.64	0.65	-0.01
Years in the village	14.19	9.91	15.27	12.70	2.56**
Social connection	0.87	0.30	0.94	0.78	0.17***
Sort seed	0.72	0.45	0.92	0.45	0.47***
Number of observations	334	334	193	141	-

Table 2: Determinants of Yield and SRI: Endogenous Switching Regression Model

	OLS		Endogenous Switching Regression					
	(1)		(2)		(3)		(4)	
	Mean Yield		Mean Yield		Variance of Yield		Skewness of Yield	
Panel A: Yield if $SRI = 1$								
Household size	-0.035	(0.025)	-0.037	(0.038)	-0.130	(0.087)	0.414	(0.349)
Married	0.371**	(0.168)	0.591**	(0.278)				
Male	-0.226	(0.170)	-0.218	(0.248)				
Men	0.081*	(0.045)	0.110**	(0.052)				
Education	0.047*	(0.027)	0.041	(0.042)	0.074	(0.105)	-0.403	(0.492)
Experience with rice	-0.002	(0.005)	-0.001	(0.006)	-0.039**	(0.015)	-0.000	(0.061)
Log wealth	0.059*	(0.032)	0.021	(0.043)	-0.002	(0.089)	-0.210	(0.278)
Total labor	0.003***	(0.001)	0.002***	(0.001)	0.004	(0.003)	0.029***	(0.011)
Chemical fertilizer	0.282***	(0.106)	-0.119	(0.226)	-0.222	(0.479)	-3.726**	(1.736)
Plot size	-0.058**	(0.029)	-0.178	(0.132)	0.130	(0.229)	0.988	(1.312)
Very fertile soil	0.024	(0.080)	0.010	(0.105)	-0.063	(0.215)	0.329	(0.671)
Slopy plot	-0.064	(0.114)	-0.298*	(0.166)	-0.264	(0.232)	-0.747	(0.802)
Plot distance	-0.013	(0.012)	-0.014	(0.023)	0.155**	(0.075)	-0.238	(0.339)
Distance to market	-0.000	(0.000)	0.000	(0.000)	-0.000	(0.000)	-0.000	(0.001)
Agriculture	0.004	(0.281)	-0.650**	(0.259)	-0.608	(0.538)	-3.802	(2.380)
Extension	0.152	(0.103)	0.072	(0.117)	0.266	(0.258)	-0.189	(1.111)
Rainfall decrease	-0.201**	(0.079)	-0.201*	(0.114)	0.136	(0.195)	-0.834	(0.707)
Temperature increase	0.194**	(0.085)	0.255**	(0.118)	0.388*	(0.204)	0.413	(0.737)
Constant	5.870***	(0.548)	7.451***	(0.734)	1.054	(1.721)	9.323	(6.761)
Panel B: Yield if $SRI = 0$								
Household size			-0.037	(0.031)	0.017	(0.030)	-0.038	(0.067)
Married			0.089	(0.131)				
Male			-0.181	(0.153)				
Men			0.079	(0.062)				
Education			0.007	(0.027)	-0.040	(0.025)	0.044	(0.054)
Experience with rice			-0.001	(0.005)	-0.002	(0.006)	0.005	(0.014)
Log wealth			0.073*	(0.043)	-0.082	(0.080)	0.078	(0.089)
Total labor			-0.001	(0.002)	-0.000	(0.002)	-0.000	(0.003)
Chemical fertilizer			-0.122	(0.233)	0.289	(0.755)	-0.915	(0.631)
Plot size			-0.024	(0.016)	0.022	(0.030)	-0.062	(0.068)
Very fertile soil			-0.109	(0.113)	0.266	(0.247)	-0.541	(0.352)
Slopy plot			0.334**	(0.130)	-0.489***	(0.176)	0.894***	(0.334)
Plot distance			-0.006	(0.009)	-0.019	(0.015)	0.033	(0.024)
Distance to market			-0.001***	(0.000)	0.001	(0.001)	-0.003	(0.002)
Agriculture			0.340	(0.269)	-0.668**	(0.307)	1.143**	(0.507)
Extension			-0.039	(0.142)	0.271	(0.293)	-0.481	(0.385)
Rainfall decrease			-0.233**	(0.115)	0.317	(0.215)	-0.832**	(0.411)
Temperature increase			0.053	(0.104)	-0.026	(0.130)	0.109	(0.232)
Constant			5.987***	(0.602)	2.102**	(1.065)	-2.154*	(1.159)

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)		(3)		(4)	
	Yield OLS	Mean Yield		Variance of Yield		Skewness of Yield	
Panel C: *SRI* **Equation**							
Household size		0.102	(0.082)	0.135	(0.082)	0.150**	(0.070)
Married		0.757**	(0.372)			0.024	(0.015)
Male		-1.909***	(0.546)				
Men		0.369**	(0.187)				
Education		0.248**	(0.099)	0.100	(0.077)		
Experience with rice		0.009	(0.014)	0.002	(0.022)	0.100	(0.070)
Log wealth		0.382***	(0.141)	0.312**	(0.146)	0.271**	(0.113)
Total labor		0.003*	(0.001)	0.002	(0.002)	0.003**	(0.001)
Chemical fertilizer		2.564***	(0.389)	2.557***	(0.484)	2.390***	(0.367)
Plot size		-1.022***	(0.293)	-0.914***	(0.297)	-0.949**	(0.412)
Very fertile soil		0.631**	(0.307)	0.753**	(0.347)	0.673**	(0.289)
Slopy plot		-0.265	(0.446)	-0.393	(0.377)	-0.225	(0.338)
Plot distance		-0.087***	(0.032)	-0.076*	(0.040)	-0.062*	(0.033)
Distance to market		0.002**	(0.001)	0.002*	(0.001)	0.002*	(0.001)
Agriculture		1.557**	(0.709)	1.445	(1.362)	1.387**	(0.625)
Extension		0.907***	(0.310)	0.765**	(0.332)	0.876***	(0.306)
Rainfall decrease		0.815***	(0.279)	0.464*	(0.256)	0.465**	(0.231)
Temperature increase		-0.644*	(0.355)	-0.444	(0.438)	-0.345	(0.358)
Years in the village		0.031**	(0.013)	0.041***	(0.016)		
Social connections		1.097**	(0.466)	1.169	(0.845)	1.258***	(0.480)
Seed sorting		1.442***	(0.296)	1.093**	(0.476)	1.015***	(0.300)
Constant		-10.323***	(2.104)	-9.015***	(2.141)	-8.295***	(2.073)
σ_1^2		0.787***	(0.119)	1.884***	(0.215)	7.562***	(0.343)
$\rho_{1\upsilon}$		-0.348	(0.213)	-0.087	(0.110)	-0.424	(0.338)
σ_0^2		0.528***	(0.079)	0.783***	(0.235)	1.781***	(0.268)
$\rho_{0\upsilon}$		-0.473	(0.395)	0.414	(1.108)	-0.675**	(0.341)
Chi Test Indep		3.036*		0.619		3.843**	
P-Value Chi test Indep		0.081		0.431		0.050	
Admissibility Tests							
Chi(3) SRI equation		27.99***		24.14***		24.66***	
P-Value Chi test		0.000		0.000		0.000	
Chi(3) Outcome equations		1.55		3.20		3.46	
P-Value Chi test		0.671		0.362		0.177	
Number of Countries	325	325		325		325	
Log Pseudo-Likelihood	-358.624	-368.002		-591.717		-958.180	

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Determinants of Income and SRI: Endogenous Switching Regression Model

	OLS		Endogenous Switching Regression					
	(1)		(2)		(3)		(4)	
	Mean Income		Mean Income		Variance of Income		Skewness of Income	
Panel A: Income if $SRI = 1$								
Household size	0.028	(0.049)	0.057	(0.060)	-0.406	(0.564)	-0.009	(0.012)
Married	0.493*	(0.273)	0.898**	(0.407)	6.151	(4.228)	0.079	(0.057)
Male	-0.018	(0.250)	-0.423	(0.341)	-0.698	(2.753)	-0.007	(0.051)
Education	0.043	(0.035)	-0.035	(0.048)	-0.306	(0.364)	-0.002	(0.007)
Experience with rice	-0.011	(0.013)	-0.021	(0.014)	-0.279**	(0.137)	-0.003	(0.002)
Log wealth	0.106	(0.086)	0.120	(0.111)	-0.104	(1.175)	-0.003	(0.022)
Total labor	0.008**	(0.004)	0.007**	(0.003)	0.137***	(0.044)	0.002***	(0.001)
Plot size	-0.024	(0.028)	0.024	(0.216)	3.845*	(2.044)	0.060	(0.058)
Fertile soil	0.424**	(0.200)	0.566*	(0.307)	3.030	(2.467)	0.036	(0.036)
Slopy plot	-0.204	(0.280)	-0.258	(0.253)	-3.090	(2.086)	-0.041	(0.029)
Plot distance	0.038	(0.025)	0.052	(0.032)	1.127***	(0.410)	0.017***	(0.006)
Distance to market	0.000	(0.000)	0.000	(0.000)	-0.001	(0.003)	-0.000	(0.000)
Agriculture	-0.883	(0.625)	-3.302***	(1.256)	-25.215**	(11.617)	-0.331**	(0.168)
Extension	0.165	(0.210)	0.255	(0.247)	0.116	(2.892)	-0.005	(0.025)
Rainfall decrease	-0.002	(0.174)	-0.177	(0.257)	-0.081	(2.552)	0.001	(0.025)
Temperature increase	0.558***	(0.163)	0.693***	(0.214)	5.221***	(1.927)	0.066*	(0.038)
Constant	-1.169	(1.269)	1.483	(1.893)	12.586	(16.256)	0.142	(0.384)
Panel B: Income if $SRI = 0$								
Household size			-0.085	(0.089)	-0.700	(0.718)	-0.007	(0.005)
Married			0.075	(0.339)	1.764	(1.704)	0.018	(0.024)
Male			0.489	(0.309)	2.220	(1.706)	0.018	(0.019)
Education			0.030	(0.033)	-0.075	(0.183)	-0.001	(0.003)
Experience with rice			0.033	(0.028)	0.270	(0.232)	0.002	(0.002)
Log wealth			0.065	(0.111)	-0.795	(0.688)	-0.007	(0.013)
Total labor			-0.007*	(0.004)	-0.037*	(0.021)	-0.000	(0.000)
Plot size			-0.052	(0.032)	-0.135	(0.183)	-0.001	(0.004)
Fertile soil			0.363	(0.243)	2.164	(1.641)	0.020*	(0.011)
Slopy plot			0.137	(0.519)	2.689	(4.214)	0.026	(0.041)
Plot distance			0.020	(0.029)	0.168	(0.179)	0.002	(0.002)
Distance to market			-0.000	(0.001)	-0.002	(0.004)	-0.000	(0.000)
Agriculture			0.720**	(0.359)	4.709	(2.879)	0.042*	(0.023)
Extension			-0.302	(0.302)	-2.786*	(1.426)	-0.023	(0.045)
Rainfall decrease			0.199	(0.261)	2.600	(1.832)	0.023	(0.018)
Temperature increase			0.347	(0.211)	0.790	(1.281)	0.011	(0.012)
Constant			-1.526	(1.180)	1.375	(6.477)	0.003	(0.104)

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)		(3)		(4)	
	Income OLS	Mean Income		Variance of Income		Skewness of Income	
Panel C: *SRI* Equation							
Household size		0.110*	(0.063)	0.109*	(0.063)	0.109*	(0.065)
Married		0.560	(0.394)	0.577	(0.396)	0.580	(0.405)
Male		-1.288***	(0.448)	-1.276***	(0.446)	-1.280***	(0.447)
Education		0.111*	(0.059)	0.111*	(0.058)	0.112*	(0.058)
Experience with rice		0.023*	(0.012)	0.023*	(0.012)	0.023*	(0.013)
Log wealth		0.252**	(0.104)	0.248**	(0.105)	0.249**	(0.106)
Total labor		0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Plot size		-1.088***	(0.290)	-1.080***	(0.288)	-1.083***	(0.289)
Very fertile soil		1.204***	(0.307)	1.189***	(0.301)	1.194***	(0.303)
Slopy plot		-0.191	(0.269)	-0.187	(0.267)	-0.188	(0.268)
Plot distance		-0.053**	(0.023)	-0.051**	(0.023)	-0.051**	(0.024)
Distance to market		0.001*	(0.001)	0.001*	(0.001)	0.001*	(0.001)
Agriculture		0.562	(0.673)	0.602	(0.652)	0.613	(0.654)
Extension		1.083***	(0.235)	1.064***	(0.233)	1.072***	(0.235)
Rainfall decrease		0.557**	(0.229)	0.552**	(0.227)	0.553**	(0.229)
Temperature increase		-0.467*	(0.249)	-0.462*	(0.250)	-0.461*	(0.250)
Social connections		1.222***	(0.373)	1.194***	(0.370)	1.194***	(0.378)
Seed sorting		1.498***	(0.253)	1.515***	(0.248)	1.514***	(0.250)
Constant		-6.357***	(1.676)	-6.350***	(1.656)	-6.377***	(1.658)
σ_1^2		1.919***	(0.197)	22.989***	(0.344)	0.358	(0.383)
$\rho_{1\upsilon}$		-0.162*	(0.096)	-0.074	(0.067)	-0.103	(0.207)
σ_0^2		1.487***	(0.184)	10.483***	(0.256)	0.094	(0.291)
$\rho_{0\upsilon}$		-0.077	(0.293)	-0.047	(0.205)	-0.041	(0.691)
Chi Test Indep		2.821*		1.225		0.249	
P-Value Chi test Indep		0.093		0.268		0.617	
Admissibility Tests							
Chi Test SRI eq.		43.66***		50.79***		50.66***	
P-Value Chi test		0.000		0.000		0.000	
Chi Test Outcome eq.		0.21		2.32		4.00	
P-Value Chi test		0.646		0.313		0.135	
Number of Countries	332	332		332		332	
Log Pseudo-Likelihood	-672.115	-735.022		-1486.371		-27.541	

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Average treatment effect on adopters and non-adopters

		Rice Yield		Total Income	
		(1)	(2)	(3)	(4)
Panel A: Treatment effects on the adopters (ATT)					
Moment	Variable	Mean	Std. Err.	Mean	Std. Err.
Type					
Mean	Adopt	7.507	(0.413)	1.577	(1.166)
	Not adopt	6.655	(0.310)	0.862	(0.837)
	ATT	**0.852*****	**(0.040)**	**0.715*****	**(0.130)**
Variance	Adopt	0.860	(0.957)	5.047	(15.468)
	Not adopt	0.919	(0.410)	-0.056	(5.586)
	ATT	**-0.059**	**(0.076)**	**5.103*****	**(1.393)**
Skewness	Adopt	0.111	(3.173)	0.054	(0.243)
	Not adopt	-2.000	(0.936)	-0.006	(0.048)
	ATT	**2.111*****	**(0.244)**	**0.060*****	**(0.020)**
Observations		188		193	
Panel B: Treatment effects on the non-adopters (ATU)					
Moment	Variable	Mean	Std. Err.	Mean	Std. Err.
Type					
Mean	Adopt	7.241	(0.641)	1.491	(1.031)
	Not adopt	6.847	(0.242)	1.130	(0.508)
	ATU	**0.394*****	**0.053**	**0.361*****	**(0.099)**
Variance	Adopt	1.384	(0.939)	11.006	(13.812)
	Not adopt	0.471	(0.355)	2.529	(3.477)
	ATU	**0.913*****	**(0.085)**	**8.477*****	**1.264**
Skewness	Adopt	5.708	(3.834)	0.150	(0.206)
	Not adopt	-0.516	(0.805)	0.015	(0.031)
	ATU	**6.224*****	**(0.354)**	**0.136*****	**(0.018)**
Observations		137		139	

Bootstrapped standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Number of replications: 10 000.

Notes

[1]By 2015, SRI has been introduced in no less than 55 countries around the world, including 22 African countries, such as Mali, Nigeria, Tanzania, and Kenya.

[2]Weeding is critical in SRI because weeds spread more rapidly under non-flooded conditions (Noltze et al., 2013).

[3]Uphoff (2006) maintains that this is a static view that does not account for the fact that labour intensity diminishes substantially once farmers have become familiar with this new approach.

[4]A number of studies point to bias in the perception of climate change associated with different factors. In line with this, Howe and Leiserowiz (2013) find that the subjective experience of local climate change is dependent not only on external climate conditions, but also on individual beliefs, with perceptions apparently biased by prior beliefs about global warming. In addition, Whitmarsh (2011) argues that individual attitudes and biased cognitive processing can also bias information recall associated with climate change. Similarly, Weber (2010) argues that recent events are likely to be given more weight than distant events in the evaluation of risky options.

[5]Each of the components is applied on almost 90 percent of the adopting plots. This is comparable to related studies (e.g. Noltze et al, 2013; Takahashi and Barrett, 2013).

[6]Temperature influences growth rate, duration, and productivity. According to Baker et al. (1992), yield decrease was about 7–8% in rice for each 1°C increase in daytime maximum/nighttime minimum in temperature from 28/21°C to 34/27°C.

[7]We bootstrap the distribution following Kim and Chavas (2003).