Socio-Economic Factors Influencing the Adoption of SRI among Smallholder Rice Irrigation Farmers in Morogoro Region, Tanzania

Mkubya R.W.[1]; P. Damas[2] and H.F. Mahoo[3]

[1]Department of Economics, Jordan University Collage, P.O. Box 1878, Morogoro, Tanzania
[2]Department of Agricultural Economics, College of Agricultural Economics and Business Studies, Sokoine Univerity of Agriculture, P.O. Box 3007, Morogoro, Tanzania
[3]School of Engineering Sciences and Technology, Sokoine Univerity of Agriculture, P.O. Box, 3003, Morogoro, Tanzania

*Corresponding author e-mail: *Mkubya@yahoo.com;* Mob: +255754893597

Abstract

This study discusses the factors that influence the adoption of the System of Rice Intensification (SRI) among smallholder farmers in the Morogoro region, of Tanzania. The overall objective of this study was to assess social economic factors affecting the adoption of SRI among smallholder farmers in Tanzania. Primary data were collected by using a questionnaire administered to farmers and a checklist for the key informants. The sample size chosen from a population of rice farmers practising in irrigation areas around Morogoro was 384 farmers. Moreover, the multistage sampling distribution was used in this study. Secondary data were collected from various books and journals from both the electronic library and Sokoine National Agricultural Library (SNAL). The logistic regression model was used in the analysis of this study: It was concluded that households accessing more extension services are more likely to participate in SRI than households with no or little extension service. The main barrier to the original use of SRI methods was the high labour demand, notably for weeding, which increased the cost of production. It would be beneficial to create various power-operated mechanical weeder models that are suited to the nation's various soil types. Incentives should be used to promote the production of mechanical weeder machines, which some farmers have been at the forefront of. A mechanized weeder reduces herbicide-related environmental damage while addressing the issues of labour scarcity and declining income per acre. Herbicides often need less labour input and have proved successful when there is a labour shortage for weeding during crucial times. It is also recommended that further research be conducted on SRI in different regions of Tanzania to broaden knowledge and to discover new techniques which will give more output by using SRI based on locality.

Keywords: Adoption of SRI, System of rice intensification, Conventional methods, Marginal effect of logistic regression.

Introduction

Rice is the second-most widely grown food and cash crop in Tanzania after maize, accounting for around 681 000 hectares (18%) of all arable land (URT, 2017). Yields are often relatively modest (1-1.5 tons/ha), as the majority is cultivated using conventional techniques. Additionally, 71% of the rice is farmed in rain-fed environments (FAO, 2010). About half of the country's rice is grown by 2 300 000 small farmers in the Tabora, Shinyanga, and Morogoro regions. The low yield is mainly brought about by the adoption of genetically low-yielding cultivars, drought, low soil fertility, weed infestations, the predominance of insect pests and diseases, and birds (FAO, 2019). Decrease in rice productivity caused by poor production techniques.

In Tanzania, both rain-fed and irrigated techniques are used to grow rice. While rain-fed rice yields range from 1.0 to 1.4 tons per hectare, irrigated rice accounts for 26% of the planted area (FAO, 2020). In Tanzania there is only 460 000 ha or 1.5% of the available land, have been used for irrigation, compared to an average of 4% for Sub-Saharan Africa (SSA), where 29.4 million hectares are thought to be suitable for agriculture (Jenes, 2019). It is estimated that only 10% of rice farmers in the nation, use certified seeds, while 90% use recycled seeds. In comparison to Kenya's and South Africa's average fertilizer usage rates of 100 kg/ha and 120 kg/ha, respectively, it is estimated that only 15% of farmers use fertilizers on a per-ha basis (John, 2018). Due to this, the country's yield of rice is low, averaging between 1.0 to 1.4 tons per hectare compared to 2.5 tons/ha for all of Africa and 4.7 tons/ha for Asia (URT, 2017; FAO, 2020).

Additionally, the National Rice Development Strategy (NRDS II) seeks to quadruple the area under rice cultivation from 1.1 million ha in 2018 to 2.2 million ha (2030) (URT, 2018). That the rice sub-sector, which is dominated by subsistence farming, is converted into a commercial and viable production system through improvements to irrigation and agronomic techniques (Low, 2021). One of the tactics being researched to increase rice output by the government and the corporate sector is the System of Rice Intensification (SRI) (John, 2018). By boosting and activating sector drivers by raising the productivity of targeted commodities, particularly rice, ASDP II's main goal is to convert smallholder subsistence farmers into sustainable commercial farmers (URT, 2018).

According to URT (2019), The National Rice Development Strategy Phase II (NRDS II) is by both national policies and international commitments that Tanzania has ratified. This is because it will be accomplished through the implementation of the four key components that support sustainable water and land use, increased agricultural productivity, and financial success. Focused on raising household earnings from rice farming, food security, and nutrition to improve the livelihood of the majority of rural populations. Moreover, URT (2017) stated that Production costs may be further decreased by using cost-effective production techniques like the System of Rice Intensification (SRI) and putting milling and processing facilities closer to the producing areas.

The System of Rice Intensification (SRI), is one of the scientific management strategies for distributing irrigation water based on soil and climate conditions (Sinha, 2019). SRI technology can enhance agricultural productivity and reduce water use (Holman and Buh, 2022). SRI techniques produce more rice per hectare than traditional agronomic techniques. SRI practices have been widely promoted globally (Barrett, 2016). The use of SRI technology is crucial for the economic growth of Tanzania's small-scale farmers. John (2018) examined SRI adoption in Northern Mozambique and discovered that farmers are more likely to adopt SRI. Zacharia (2013) claims that even if SRI is more effective than conventional methods, acceptance and dissemination in Tanzania have been delayed due to a lack of enough extension services.

Many empirical studies have investigated the issue of crop productivity and profitability (Denkyirah, 2015). Adoption of SRI practices necessarily changes the mix and allocation of inputs in particular of water, seeds, fertilizers and labour (Berkhout *et al.,* 2015). However, SRI impact studies have generally failed to distinguish between technological changes, more productive use of inputs, and evidence by change in factor productivity, increase input use or selection effect and their respective effect on yields (Katambara *et al.,* 2013).

In addition, Takahashi and Barrett (2014), reveal that SRI impact on yields may result from varying degrees of adherence to SRI practices, which are tested, and adopted by farmers in local conditions. Denkyirah (2015), stated that the system of rice intensification (SRI) is being promoted worldwide but relatively little is known about its impact and farm level. Its slow uptake by smallholder farmers raises questions about whether this new rice production method is economically viable and increases the net benefit to farmers. Despite several promising benefits offered by SRI as revealed in several studies, there is limited empirical evidence on determinants affecting the decisions to adopt individual as well as the combinations of SRI (Katambara *et al.,* 2013). However, the factors influencing the adoption as well as adoption impacts have been a subject of debate (Moser, 2022). The variation in adoption, yield, costs, and profitability in rice production methods is attributed to the characteristic of the farms, ecological differences, and implementation (Low, 2022). Although attempts are being made to adapt SRI for farmers, there is little empirical data on the factors that influence SRI adoption in Tanzania.

The characteristics of the farms, ecological variances, and implementation techniques are responsible for the variety in adoption, yield, costs, and profitability in rice production systems (Drez, 2018). Despite several empirical documents on SRI and several potential advantages it provides, there is a dearth of empirical data on the factors influencing the adoption of its constituent parts and their effects on yield for smallholder rice farmers in the Morogoro Region. Among farmers using SRI, only 37% adopted a full package comprising plant, soil and water management practices. Plant management only is the least adopted SRI component, being used by only 17% of SRI adopters (Dorosh, 2015). Therefore this study aims to investigate determinants of the adoption of SRI among small-scale rice farmers in the Morogoro region, Tanzania. Morogoro region is chosen because is surrounded by many irrigation schemes practising SRI.

Theoretical Framework

Contingent Partial Adoption Framework for New Technologies

The model represents the farmer's choice as a discrete option. The farmer can decide whether or not to take part in an irrigation project. Farmers contributing to irrigation project is as follows: $\alpha=0$ for the case of not contributing and $\beta=1$ for the case of contributing. Assume the farmer R produces a single output Y at price I. In this instance, rice is the outcome. The production function f(Z) is twice differentiable and assumes continuity. S is a vector of input prices, while Z is a vector of inputs. In the input and output markets, farmers act as price takers, and it is believed that all prices are not arbitrary. Water γ is assumed to be a crucial input in the production practice. δ is the basis of additional inputs like seed, labour, fertilizer, and agrochemicals. Using the assumptions mentioned above, the production function may be expressed as in equation 1:

$$Q=f(\gamma,\delta) \quad \ldots\ldots\ldots\ldots\ldots\ldots(1)$$

then, before adoption, a farmer's productivity function is $Q=f(\gamma_0,\delta_0)$ and after the adoption is $Q=f(\gamma_1,\delta_1)$. As shown by Equation 1, Productivity is impacted by the availability of water and other inputs. Water inputs are considered to be the key component in agricultural output since it differentiates between irrigated and rain-fed areas. The change in the production function (ΔY) The following equation shows what has happened as a result of the use of irrigation (Equation 2).

$$\Delta Y=Q=f(\gamma_1,\delta_1)-f(\gamma_0,\delta_0) \quad \ldots\ldots\ldots(2)$$

Adoption must satisfy the criteria $\Delta Y>0$. In other words, irrigation will boost production while using the same amount of input.

As an alternative, fewer inputs can nevertheless provide the same level of output. A farmer must pay a large amount of money to participate in an irrigation project, which in the context of this research includes irrigation water fees, membership fees, and other expenses related to the scheme. for the participants C>0 and the non-participants C=0. The profit maximization function of the irrigation farmer is calculated (Equation 3):

$$\text{Max Profit } 1=\text{Max}[pf(\gamma_1,\delta_1)-Z_1\,\gamma_1-Z_1\beta_1 \ldots\ldots\ldots(3)$$

The first-order condition for irrigation water input derived from Equation 3 is in equation 4:

$$\frac{\delta(\gamma_1,\delta_1)}{\delta\gamma}=\frac{Z}{\beta_1} \quad \ldots\ldots\ldots(4)$$

Equation 4 demonstrates that the water's anticipated marginal productivity is equal to the difference between its input and output prices. The producer's choice to take part in an irrigation project will formally confirm the following disparities (Equation 5).

$$E[\mu(Profit1)-E[\mu(Profit\ 0)]>0 \quad \ldots\ldots\ldots(5)$$

Therefore, farmers only use irrigation when it may increase their predicted usefulness and profit over what it would be without it. So, farmers only utilise irrigation when it has the potential to boost their expected utility and profit beyond what they would otherwise achieve.

Methodology

Geographical Location

Morogoro Region is one of the 30 Regions in Tanzania's Mainland. The Region lies between latitude 5 58" and 10 0" to the South of the Equator and longitude 35 25" and 35 30" to the East (Fig. 1). It is bordered by seven other Regions. Arusha and Tanga regions to the North, the Coast Region to the East, Dodoma, and Iringa to the West, and Ruvuma and Lindi to the South. Morogoro Region occupies a total of 72,939 square kilometres which is approximately 8.2% of the total area of Tanzania's mainland (URT, 2017). Administratively Morogoro region has five districts. The districts are divided into thirty divisions, these in turn are further subdivided into 140 wards. There are 457 villages in the region. Ulanga district is the largest, with 33.6 per cent of the total regional area, but it is the one with the least number of villages (14.2 per cent of the total). Morogoro Rural has most of the divisions (33%), wards (30%), and villages (47%) (NBS, 2013). The area is chosen because it has very potential for rice production supported by big irrigation schemes in Kilosa District, Kilombero District, Mvomero District, and Morogoro Rural District are focus areas for SRI projects.

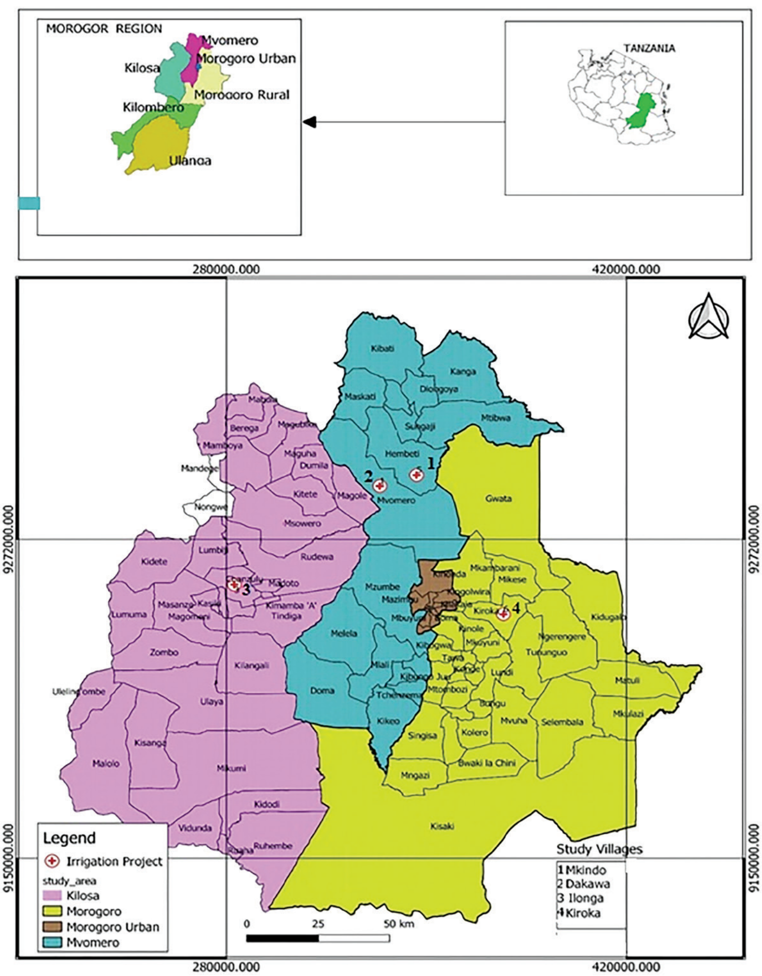

Figure 1: The map of the Morogoro Region showing study Locations

Research Approach

Data were collected through the use of a questionnaire and checklists after a preliminary survey that aimed at familiarizing the researcher with the study area and pre-test the questionnaire to gauge the relevance of the questions and its comprehensiveness. The questionnaires were used to collect primary data from farmers and were administered during the survey through personal interviews. The checklists were used to collect data from key informants to supplement the information obtained from interviews.

Population

According to national census statistics from 2022 (NBS, 2022), the Morogoro region has 3,197,104 residents. It is made up of the following districts: 617032 Kilosa, 471409 Morogoro Municipality, 421741 Mvomero, 387736 Morogoro, 292536 Mlimba, 258205 Gairo, 23289 Ulanga, 225126 Malinyi Districts, and 290424 Ifakara Town Centre. The region experienced an average annual population growth rate of 2.4% from 2012 to 2022, which matched it for the fifteenth highest in the nation. In terms of population density, it ranked 22nd, with 31 inhabitants per square kilometre. Due to its urban qualities, which draw many individuals looking for work in industries and nearby business prospects as well as services, hotels, offices, etc., the Kilosa district has an extremely high population.

Sampling Technique

The study adopted a multistage sampling method because it is more flexible than one-stage sampling. This method improves the likelihood of selecting a more efficient sample and is convenient for small populations. The sampling techniques were implemented in two stages: The first sampling stage involved the selection of three Districts (Kilosa, Mvomero and Morogoro Districts) within the Morogoro region. The district was selected based on the criteria that they have irrigation schemes and also practice SRI projects on those schemes.

Secondly, four wards were purposively selected: Hembeti and Dakawa in the Mvomero district, Chanzuru in the Kilosa district and Kiroka in Morogoro District. Furthermore, four villages were purposively selected (Kiroka in Morogoro District, Dakawa and Mkindo in Mvomero District and Illonga in Kilosa District). Then, 96 randomly chosen farmers (48 using SRI and 48 using the conventional approach) from each of the four villages mentioned above, creating a sample size of 384 farmers. Wards and villages selection was based on the conditions that they have irrigation schemes and implemented SRI projects in those schemes. The criteria for the farmer to be an SRI farmer is the Use of an improved variety of seeds, the Use of uprooted seedlings for 8 days on an SRI farm, drying and wetting the land, weeding at least two times, applying fertilizer twice. Farmers are referred to as Progressive SRI Farmers when they meet the criteria for practising SRI and are constantly engaged in farming.

Estimation of a sample size

This study opted to use the proportion sample statistic to estimate the sample size of farmers using SRI and those using conventional methods in the Morogoro region. Below is the proportion sample statistic that was used to determine the sample size.

The confidence level corresponds to a Z-score

This is a constant value needed for this equation 6. Here are the z-scores for the most common confidence levels: 90% – Z score = 1.645; 95% – Z score = 1.96; 99% – Z score = 2.576

*Sample Size = (Z-score)² * StdDev*(1-StdDev) / (margin of error)²* ....(6)

Here is the calculation works assuming when choosing a 95% confidence level standard deviation is equal to 0.5 and a margin of error (confidence interval) is +/- 5%.

$((1.96)^2 \text{ x } 0.5(0.5)) / (0.05)^2$

$(3.8416 \text{ x } .25) / 0.0025$

$0.9604 / 0.0025$

384.16

384 respondents are needed

Data analysis

Logistic Regression Model

The logistic regression model was chosen, as this model is frequently used to analyse multivariate data with binary responses. This approach presupposes that a person has a choice between adopting SRI and not (Sanders, 2014). Based on continuous and categorical independent variables (Table 1), logistic regression is used to predict a dependent variable's SRI and to calculate the proportion of the dependent variable's variation that is explained by the independent variables (Mellor, 2017). The maximum likelihood estimate is used in logistic regression after the dependent is changed into a logit variable (Chianu, 2018). In this manner, logistic regression calculates the likelihood that a specific event will occur. Mayong (2019) claims that determining the parameters that maximize the probability (likelihood) of the sample data is how maximum likelihood parameter estimation is obtained. This approach is thought to be more reliable and produces estimators with good statistical characteristics. In other words, maximum likelihood estimation methods are flexible and used with many types of data and logistic regression models (Equation 7). The technique is also effective at quantifying uncertainty using confidence bounds (Nyariki, 2011).

P and Y = 0 is referred to as 1-P

$$ln\left(\frac{p}{1-p}\right) = \beta 0 + X_1\beta 1 + X_2\beta 2 + X_3\beta 3 + X_4\beta 4 + X_5\beta 5 + \cdots \varepsilon \quad (7)$$

Where:

β0 = Constant

X1= Age of respondent

X2 = Gender of respondent

X3 =Education

X4= Household size (last yr)

X5= Access to credit

X6= Access to extension service

X7 = Cultivated land size

e = Random error

Marginal effect estimation for predictors in the logistic regression model

The marginal effect of a predictor in a categorical response model estimates how much the probability of a response level changes as the predictor changes (Moser, 2022). For a continuous predictor, the marginal effect is defined as the partial derivative of the event probability concerning the predictor of interest (Tobin, 2016). For a binary categorical predictor, it is the change in event probability when the predictor is changed between its levels (Sinha, 2017).

As a derivative, the marginal effect is the slope of a line drawn tangent to the fitted probability curve at the selected point. It is the instantaneous rate of change of the probability at that point. Note that the marginal effect depends on the predictor setting that corresponds to the selected point at which this tangent line is drawn, so the marginal effect of a variable is not constant. A measure of the overall effect of the predictor is the average of the marginal effects (AME). An alternative overall measure is a marginal effect evaluated at the mean of all of the predictors (MEM). For small samples, the AME is considered the better measure.

Note that if the fitted probability curve is approximately linear (as it is near p=0.5) at the selected point, then the tangent line will closely approximate the fitted curve and the marginal effect will closely approximate the change in probability when changing the predictor by a fixed amount such as one unit. But in areas where the curve is nonlinear (near the smallest and largest values of p), the marginal effect might deviate substantially from the change over a fixed amount.

For a categorical predictor, the derivative is not strictly defined. In this case, the marginal effect is measured by the change in predicted probability between its levels (Richard, 2012). For a binary logistic main effects model, logit(p)=Σixiβi , the marginal effect of xi is equal to p(1–p)bi , where p is the event probability at the chosen setting of the predictors and bi is the parameter estimate for xi (Stockle, 2010) . Vatin (2016) explained that suppose the possible response values are ordered with levels i=1,2,...,k. Under the ordinal logistic model (proportional odds model), the probability of response level i is the difference in the cumulative probabilities at level i and level i-1 (Equation 8).

pi = F(αi+x'β) - F(αi-1+x'β) ....(8)

Where αi is the ith intercept, β contains all non-intercept parameters, and F(x) is the logistic

Table 1: Prior expectations for the signs of parameter coefficients

Variable		Measurement	Description	Expe sign
X1	Gender (Dummy)	Dummy (0=Female, 1= Male)	Male farmers are more likely to adopt the use of SRI's compared to female farmers	+
X2	Age	In years (continuous)	Younger farmers are more likely to adopt than older farmers.	+
X3	Education	1= informal education 2= primary education, 3= secondary education, 4= above secondary education (Categorical)	Formal-educated farmers are more likely to adopt than those with informal education levels	+
X4	Cultivated land size	In hectares (Categorical)	Large farm-size owners are more likely to adopt the use of SRI's compared to small farm-size owners	+
X5	Household size	Household member (Categorical)	Large household size are more likely to adopt SRI than small household size	+
X6	Credit Access	Dummy (0= Access to Credit or 1= not accessing credit)	Good credit accessibility encourages the adoption of SRI	+
X7	Access to extension	Dummy (0= Access to Extension or 1= not accessing Extension services)	Good accessibility of extension services encourages the adoption of SRI	+

cumulative distribution function F(x)=exp(x)/(1+exp(x)). then the marginal effect of the jth predictor, xj,on pi is (Equation 9)

$$\frac{\partial p_i}{\partial x_j} = \frac{\partial x'\beta}{\partial x_j}[p_i(1-p_i) - p_{i-1}(1-p_{i-1})] \text{......(9)}$$

For a model containing only main effects,

$\frac{\partial x'\beta}{\partial x_j} = \beta j$ as in the binary logistic model (Bamberg, 2014). Improved technology adopted were: Improved rice seed variety, improved line spacing, improved planting depth, uses of agrochemicals, Fertilizers application, mechanized harvesting, improved nursery, timely transplanting, and dry and wetting of the Land

β0 = Constant
βi = Parameter coefficients
X1= Age of respondent
X2 =Education
X3 = Income of the farmer
X4= Household size (last yr.)
X5 =Farm size
X6= Marketing Access
X7 = Access to Credit
X8 = Market Access
e = Random error

Results and Discussion
General Information
Sex of Respondents

Results in Table 2 show that for interviewed respondents using SRI males and females were 78.6% and 21.4% respectively while for interviewed respondents using conventional methods males and females were 60.9% and 39.1% respectively. According to respondents who used the SRI approach and the conventional method, males make decisions and work on the farm in a typical family where all the members are present. The results in Table 1 indicated that according to respondents who used the SRI approach and the conventional method, males make decisions and work on the farm in a typical family where all the members are present. The decision-making for family care falls primarily on women. In a household (Scheme) where the guy works outside the region, the woman makes decisions regarding farming, as well as regarding family care (especially with caring for children and the elderly), cooking, and managing household finances. The husband must return remittance from employment outside the agricultural sector to the wife in the community for use in financing farming and supporting the family. According to Peden's (2021) findings, the majority of men are likely to be male because, in the majority of poor Tanzanian families, men are in charge of family activities involving cash transactions while women are in charge of taking care of their homes and children and, as a result, devote most of their time at home. Additionally, since women, particularly in developing nations, do not have equal access to means of production like farms and support services like loans, access to capital may be another factor contributing to this pattern.

Education level

The findings presented in Fig 2 show that the majority (78.6 %) and (70.3 %) of the respondents using the SRI and Conventional methods respectively, had primary education. This suggests that rice farmers in the study area possess foundational knowledge that can be applied to raise the level of rice production. Results in Figure 2 imply that In general, those with primary education make up the majority of the labour force in all irrigation schemes (Illonga, Kiroka, Dakawa, and Mkindo). The majority (78%) of farmers find it difficult to complete secondary education due to the significant level of poverty. Additionally, the absence of educational facilities and teachers is a significant difficulty for those who can continue with secondary education. According to studies cited by Lopes (2019), a lack of education limits farmers' ability to be innovative while implementing SRI. According to Assucao (2018), the high percentage of persons enrolled in formal education may be due to the country's obligation that all citizens complete basic school education. This shows that SRI farmers possess a fundamental understanding that can be used to increase the amount of rice production in the study area.

Table 2: Sex of Respondents practicing either SRI or Conventional Irrigation methods

Gender	SRI (%, n = 192)	Conventional (%, n = 192)
Male	78.6	60.9
Female	21.4	39.1
Total	100.0	100.0

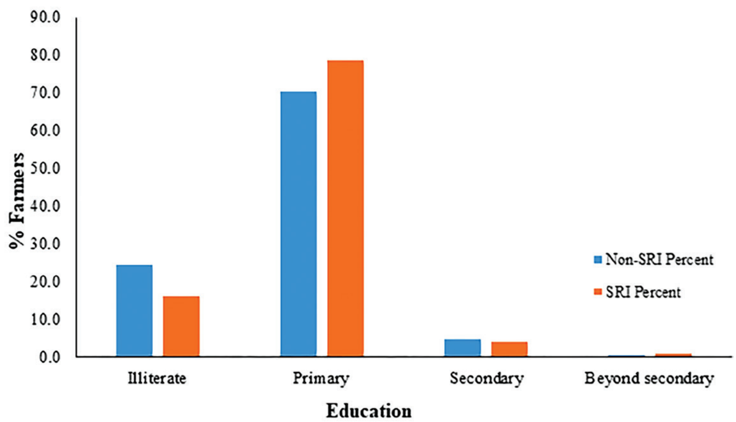

Figure 2: Education level of a respondents

Age of respondents

The findings in Table 3 show that the average age of responses from farmers that use SRI is 32 years old, with a minimum age of 26 and a maximum age of 75 years. Farmers who employ the conventional approach are typically 31 years old, with a minimum age of 22 and a maximum age of 67. Implies that younger farmers are more prepared to take risks than older farmers and have longer planning horizons. Many respondents were under the age of 25, which suggests that the majority of them would prefer to reside close to irrigation schemes where they could obtain basic social amenities. Kealy (2017) demonstrated how age structure can be utilized to help assess the labour potential of a particular population. This implies that SRI is carried out by the economically active segment of the population as the majority of SRI farmers were of working age.

Table 3: Descriptive statistics on the age of respondents

Details	SRI(n=192)	Conventional Method (n=192)
Mean	32	31
Minimum	26	26
Maximum	75	67
Standard Deviation	1.7075	1.5811
Sample Variance	2.91556	2.4999

Adoption of Technology

Socio-economic Factors that Influence SRI Adoption

The probability of a household adopting SRI is estimated using the logit model. The variables included in the model were: Age of respondents, gender, education, marital status, household size, distance to the farm, information technology, transportation, cultivated land size, planting materials, marketing access, access to extension services, and storage facilities. The estimation results are presented in Table 3 below. To identify the factors that influence household participation in SRI in the study area, the Logit model was used to generate propensity scores for the matching algorithm.

Sex

The results in Table 2 show that The Logit estimates indicate that the gender of the farmer is significant at a 10% level and has a positive sign implying that male is more likely to adopt the use of SRI technology than their female counterparts. This shows that male farmers have better access to information and other resources on improved SRI technology and are more likely to adopt new technology than their females. This result is in agreement with Chen (2017), Rather (2015) and Carson (2017)

Household Size

The results in Table 4 show household size was statistically significant (at the 1% level of significance) and it is positively associated with the probability of participation in SRI farming. The possible reason is that households with larger family sizes can probably have more labour to engage in SRI. Since households with larger household sizes can perform various SRI activities without labour shortage. Hence, households with larger household sizes can probably choose to participate in SRI farming in the area. This result was supported by Chen (2017) who found that with a unit change in the household size of the household, the probability of participation would increase by 2%. Other variables in the model remain constant at their mean value. Household size positively increases the probability of participation in SRI farming. This suggests that the increase in household size implies cheap labour and a higher chance to participate in SRI schemes.

Cultivated Land size

The results in Table 4 indicate that households with large cultivated land sizes were less likely to participate in the SRI scheme. This was shown by the negative coefficient of cultivated land size and was significant at a 5% significance level. It implies that SRI need close supervision and land to produce large amounts of rice. Large cultivated land size is not effective for SRI because it is difficult to manage weeding and supervision of labour and water management.

Access to Credit

The results in Table 4 show that household size was statistically significant and positive at the 5% level of significance. Implies that farmers with credit availability have higher opportunities to engage in SRI farming. Access to credit played an important role in improving household livelihoods. Results supported by Dorosh, (2015) found that households with access to credit purchased more inputs (fertilizer, improved seed variety, agrochemicals) than those without. Access to credit also ensures that farmers can secure inputs in time. This leads to improved agricultural output, resulting in increased farm income.

Education

The results in Table 4 show that the education variable positively influenced the adoption of SRI technology by rice farmers in the study area at a 10% significance level. It indicates that the higher the level of education of an SRI Farmer, above secondary school-educated farmers are likely to adopt SRI followed by farmers who graduated from secondary schools, primary schools and informal education. This means that higher-educated SRI farmers can easily access SRI technology followed by secondary school graduates, Primary school graduates and then informal educated farmers. This result is similar to the observation of Mellor (2014) as they found out that a positive association exist between levels of farmer's education and adoption.

Access to extension services

The results in Table 4 show that the Extension contact variable was significant at a 10% significance level and had a positive effect on improved SRI technology adoption. The positive effect of extension services shows that households who get more extension services are more likely to participate in SRI than households with no or little extension services. This result is similar to that of Lopes (2019) found a positive association between extension accesses and improved rice technology adoption. The more extension agents visit farmers and introduce or educate them on the benefits of adopting new improved technologies, the greater the likelihood for farmers in adopting new technologies. Studies conducted by Mukta (2015), reveal that better access to information from extension agents significantly affects adoption. Joseph, (2014) also endorses this by concluding their research work that it is important to enhance the activities of extension officers because they have a positive influence on technology adoption. Kealy, (2003) also found that extension officers perform an important task by sending information on the adoption of technologies to farmers and for enhancement in crop cultivation.

The marginal effects of the logit regression

(See Table 3 on the appendix page)

Table 4: Logit model predicting the probability of SRI participation. Propensity score estimation results

Variable	Coefficient	Std Error	t	P>│t│
Constant	1.06992	1.8395	0.5816	0.280761
Sex of respondent	0.118907	0.0469	2.5353	0.006018*
Age of respondent	1.16672	1.4822	0.7871	0.216099*.
Education	0.105542	0.0317	3.3279	0.000525*
HH size	1.502537	0.424	3.5434	0.0005***
Cultivated land size (acre)	-1.60322	0.5209	3.0776	0.001197**
Access to credit	1.773062	0.5173	3.4274	0.000373 **
Access to extension	0.74119	0.3269	2.2677	0 .012234**

Note: *** significant at 1%, ** significant at 5% and * significant at 10% of significance levels

The results on the Marginal Effects of the Logit Regression are shown in Table 5. A marginal effect of an increase in the age of SRI farmers decreased the likelihood of using agrochemicals by 0.0218 (2.18%), mechanized harvesting by 0.001 (0.1%), and new weeding technology by 0.0052 (0.52%). The adoption of these technologies is thought to be negatively associated with age. Younger individuals are more efficient than older people at using agrochemicals, mechanical harvesting, wetting and drying, and new weeding technologies because they are more vivacious and engaged in their education. Older farmers, however, are less likely to accept these technologies because they lack confidence in their capacity to understand and effectively employ these techniques. This agrees with Elias (2015), that Age was found to be inversely associated with the likelihood of participating in SRI. The uptake of improved nurseries and timely transplanting is otherwise increased by 0.013 (0.13%) for every unit increase in age. This indicates that older farmers have more experience than younger farmers in nursery preparation. Moreover, Nyariki (2018) and Yap (2016), discovered that a farmer's older age enhanced the likelihood of using an improved nursery by 0.11% and the likelihood of timely transplanting by about 0.4%.

The likelihood of farmers adopting new rice varieties slightly increased by 0.0015 (0.015%), planting depth by 0.012 (0.12%), agrochemicals by 0.0028 (0.028%), fertilizer by 0.00004 (0.004%), mechanical harvesting by 0.00027 (0.0027%), improved nurseries by 0.00068 (0.068%), and new weeding technology by 0.00005 (0.0005%) for every unit increase in farmers' income. It implies that wealthy farmers may be less risk-averse and have access to more cutting-edge technologies than less wealthy farms. Powel (2017), Yao (2017), and Zilberman (2015) found that a farmer may access the use of SRI by 0.000059% with an increase in income. This means that as a liquidity element, the more the farmers have access to a source of financing, the more likely they are to employ rice-improving technology that may boost crop production.

The likelihood of adopting improved rice seed varieties increased marginally by 0.00126 (0.126%), improved line spacing by 0.032 (3.2%), planting depth by 0.031 (3.1%), fertilizer by 0.0042 (0.42%), and wet and drying of the field by 0.012 (1.2%) for the SRI farmers. Adoption of SRI was positively correlated with household size. Implies that the likelihood that farmers will adopt SRI increases with household size. The fundamental rationale is that large families can contribute more work to the farming process. The finding reinforced by Wichelns (2013) suggests that household size improves the likelihood that these technologies will be adopted, which may be because rice production technologies need more labour from the farmer, which is typically supplied by his or her household members. According to Knight (2015), as the family size rises, the likelihood of adoption rises as well. This suggests that larger households offer the necessary agricultural labour related to the usage of new technology.

The farmers' education was helpful and important in increasing their propensity to use better rice varieties, agrochemicals, fertilizer, mechanized harvesting, improved nurseries, timely transplanting, and wetting and drying techniques. According to the findings, farmers were more likely to adopt improved rice seed varieties by 0.015 (1.5%), agrochemicals by 0.085 (8.5%), fertilizer by 0.013 (1.3%), mechanized harvesting by 0.0055 (0.55%), improved nurseries by 0.621 (6.2%), timely transplanting by 0.0002 (0.02%), and wet and dry by 0.014 (1.4%) when their number of years in school increased by one unit. It suggests that educated SRI farmers have the human capital to comprehend and use information more thoroughly than those without management experience. Farmers that have received education are better able to comprehend and quickly embrace new technologies. Weir (2010) also found that education increases farmers' capacity to accept agricultural innovation, which boosts production and efficiency.

The likelihood of adopting enhanced rice seed types, improved line spacing, agrochemicals, fertilizer, mechanical harvesting, wetting and drying, and weeding technologies was negatively correlated with farmers' land area under cultivation. According to the findings, the likelihood that farmers will adopt

Table 5: The marginal effects of the logit regression

Variable	New rice seed varieties	Improved line spacing	Planting depth	Use of agrochemicals	Fertilizer	Mechanized harvesting	Improved nursery	Timely transplanting	Wetting and drying	Weeding technology
Age	0.00256(0.42)	-0.0013(-0.32)	-0.0141(-1.12)	-0.0218(-3.66)**	0.002(0.52)	-0.001(-2.41)**	0.113(2.17)**	0.001(3.15)**	-0.012(-2.14)**	-0.0052(-2.44)**
Income	0.0015(2.17)***	-0.0005(-0.43)	0.012(3.23)**	0.0028(1.84)*	0.000041(4.32)***	0.0055(1.66)*	0.00068(1.15)*	-0.00067(-2.03)	-0.00035(-0.16)	0.00027(7.12)**
Household size	0.00126 (4.11)**	0.032(3.19)**	0.031(1.24)**	-0.010(-1.21)	0.0042(1.140)**	-0.002(-0.31)	-0.123(-1.13)	0.0002(0.04)	0.012(3.22)**	-0.002(-0.13)
Education	0.015(1.51)*	-0.012(-1.41)	0.00006(0.08)	0.085(3.94)***	0.013(1.070)**	0.0055(1.63)*	0.621(1.31)***	0.0012(1.02)**	0.014(1.05)***	-0.001(-0.12)
Farm size	-0.103(1.12)**	-0.040(1.66)**	-0.016(-2.74)***	0.132(1.33)**	-0.026(1.120)**	0.040(1.34)*	-0.214(-0.45)	-0.004(-0.35)	-0.061(1.22)**	-0.113(1.56)*
Marketing Access	0.002(0.13)	-0.006(-0.04)	0.045(1.18)**	-0.012(-0.712)	-0.007(-0.17)	-0.004(-0.45)	0.678(3.14)**	0.087(1.81)*	-0.005(-0.619)	0.006(0.56)
Access to credit	-0.045(-0.84)	-0.0003(-0.01)	0.029(2.63)***	-0.014(-0.35)	0.201(3.99)*	0.010(0.31)	0.019(0.64)	0.002(0.16)	-0.037(-0.79)	-0.091(-0.25)
Extension	0.013(1.72)**	0.012(3.05)**	0.01255(1.93)*	0.0169(1.83)*	0.029(1.66)*	0.0134(2.25)**	0.145(2.31)**	0.027(1.91)*	0.013(1.25)**	0.1512(3.04)
Pseudo R^2	0.1421	0.1539	0.4118	0.2409	0.1325	0.3020	0.4467	0.4533	0.4233	
Likelihood Chi-square	22.70***	30.53***	80.66***	44.85***	33.45***	20.36***	45.20***	48.12***	72.64***	55.12***

Values in parenthesis are z-values; ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level;

improved rice seed varieties decreases by 0.103 (10.3%), improved line spacing by 0.040 (4%), agrochemicals by 0.132 (13.2%), fertilizer by 0.026 (2.6%), mechanized harvesting by 0.040 (4%), wetting and drying by 0.061 (6.1%), and weeding technology by 0.113 (11.3%) for every additional hectare they cultivate. It implies that the size of the farm greatly reduced the likelihood of planting depth adoption. The likelihood of implementing the appropriate planting depth for rice production is reduced by 0.016 (1.6%) for every case of an increase in farm size.

The adoption of better rice production technology was positively impacted by contact with extension agents across the board, demonstrating that extension contact increases the likelihood of adoption. The findings indicate that a unit increase in the number of visits by extension agents to farmers increased the likelihood of adoption of improved rice seed varieties by 0.013 (1.3%), improved line spacing by 0.012 (1.2%), improved planting depth by 0.01255 (1.255%), use of agrochemicals by 0.0169(1.69%), fertilizer by 0.029 (2.9%), mechanized harvesting by 0.0134 (1.34%), improved nursery by 0.145 (1.45%), timely transplanting by 0.027 Farmers that have strong relationships with extension agents are more likely to be familiar with the various production-boosting management techniques.

Conclusions

The study managed to establish factors that are important in influencing individuals' chances of adapting to SRI, and these include: Education, household size, cultivated land size, market access, and credit access were significant. Farmers accessing more extension services are more likely to participate in SRI than Farmers with no or little extension service. The increase in household size implies cheap labour and a higher chance to participate in SRI schemes. Young people are more effective in using agrochemicals, mechanized harvesting, Wetting and drying, and new weeding technology than old people because they are energetic and more active in learning. While older farmers are less likely to adopt these technologies because they are simply not confident in their ability to learn about and properly use these technologies. Market access is very important in SRI improvement. Educated farmers have high ability to understand and easily adopt new technologies than an uneducated one.

The main barrier to the original use of SRI methods was the high labour demand, notably for weeding, which increased the cost of production. It would be beneficial to create various power-operated mechanical weeder models that are suited to the nation's various soil types. Incentives should be used to promote the production of mechanical weeder machines, which some farmers have been at the forefront of. A mechanized weeder reduces herbicide-related environmental damage while addressing the issues of labour scarcity and declining income per acre. Herbicides often need less labour input and have proved successful when there is a labour shortage for weeding during crucial times. It is also recommended that further research be conducted on SRI in different regions of Tanzania to broaden knowledge and to discover new techniques which will give more output by using SRI based on locality. The extension services can be intensified by promoting the linkage between farmers, researchers, and extension personnel. The current existing irrigation policy in promoting irrigation farming in Tanzania should be improved by the policymakers to increase SRI adoption in Tanzania.

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References

Assoucao, H. F. (2018). Real or Imagined Water Competition? The case of rice irrigation in the Usangu basin and Mtera/Kidatu hydropower, Tanzania. 10pp.

Barret K. (2016). An Economic Analysis of Modern Rice Technology and its Adoption Behaviour in Tamil Nadu. Agricultural Economics Research Review, 22:341-347.

Berkoff, J. (2013). Water Resource Management in Asia. World Bank Technical Paper No. 212. Washington, D.C.

Carson, R. (2017). Using Surveys to Value Public Goods: The Contingent Valuation Method, Resources for the Future. Resources for the Future Washington DC. 488pp.

Chen, Z. (2017). The relation- ship between farm size and productivity in Chinese Agriculture. Paper prepared for presentation at the American Agricultural Economics Association An- nual Meeting, Rohde Island, July 24-27, 2005.

Chianu, J. (2018). Determinants of Farmer's Adoption and Adaptation of Alley Farming

Denkyirah, R.W. (2015). Economic and Social Analysis of Projects and of Price Policy: The World Bank Staff Working Paper No. 369. 65pp.

Dorosh, P.A. (2015). Food Aid and Food Security in the Short and Long Run: Country Experience from Asia and sub-Saharan Africa Food Aid and Food Security in the Short- and Long Run. SP discussions paper no 0538. 122pp.

Drez, A. (2018). Theory of Production. A Long-period Analysis. Cambridge University Press, UK. 650pp.

FAO (2010). Agricultural Research and Modern Varieties. [https://www.fao.org/3/V4200E/]. Site Visited at 29/05/2023

FAO (2019). The State of Agricultural Commodity Markets. Rome, Italy. 150pp.

FAO (2020). Globalization of Food Systems: Impacts on Food Security and Nutrition. Rome, Italy.60pp.

John, A. (2018). "Economic Efficiency of small scale food crop production in Nigeria: a stochastic frontier approach. *Journal of Social Sciences*, 14(2), pp. 123–130.

Joseph, O. (2014) Determinations of Total Factor Productivity with Cob – Douglas production function in Agriculture. *Journal of Applied Sciences* 7: 499 – 501.

Katambara, Z., Fredrick, C.H., Mahoo, H., Winfred, B.M., Fikiri, M., Paul, R., Muyenjwa, M. and Anthony, N. (2013). Adoption of System of Rice Intensification (SRI) in Tanzania. [http://dx.doi.org/10.4236/as.2013.4856] Site was Visited on 9/10/2014.

Kealy, R. (2017). Inverse productivity: land quality, labour markets, and measurement error. *Journal of Devel- opment Economics,* 71: 71-95

Knight, J. (2015). Education Externalities in Rural Ethiopia: Evidence from average and stochastic frontier production functions. Working Paper No. 4. Centre for the Study of African Economies, University of Oxford, UK.117pp.

Lopez, K. (2019). Farm water and rural poverty reduction in developing Asia. Irrigation and Drainage. 56: 127–146.

Lopez, M. (2019). Rice Biotechnology: Improving Yield, Stress Tolerance and Grain Quality, P. 1-10. Novartis Foundation, John Wiley and Sons Ltd. 243pp

Louw, A., Emongor, R.A., Kirsten, J.F. and Madevu, H. (2021). Recovering Markets: Securing Small Producer Participation in Restructured National and Regional Agri-Food Systems. Oxford University Press, Oxford, U.K. 150pp.

Mayong, T. (2019). Explaining Productivity Variation among Smallholder Maize Farmers in Tanzania. Proceedings of the 12th World Congress of Rural Sociology of the International Rural Sociology Association. Goyang, Korea. 33pp.n

Mellor, J.W. (2017). Faster More Equitable Growth: The Relationship between Growth in Agriculture and Poverty Reduction. A Conference Paper Presented At Harvard Institute For International Development. Cambridge, USA. September 2016. 33pp.

Moser, C.M., and Barrett, C.B. (2022). The disappointing adoption dynamics of a yield-increasing, low external-input technology: the case of SRI in Madagascar. Agricultural

Systems,76(3), 1085-1100.

Mukta, K.P. (2015).Climate information applications for sustainable development in Africa.Tudor Rose Publishers, Geneva, Switzerland. 163pp.

Nyariki, N. (2018). Measuring the impact of user participation in agricultural and natural resource management research. Agricultural Systems 78(2): 287 – 306.

Powel, M.S. (2014). Population Distribution in Tanzania. Government Press, Dar-es-salaam, Tanzania. 80 pp.

Richard, W. (2012). Using the margins command to estimate and interpret adjusted predictions and marginal effects. 12:308–331, 2012.

Sanders S. (2014). Agricultural Intensification: The Status in Six African Countries. World Bank Policy Research Working Paper No. 7116.

Sinha, S.K. and Talati, J. (2019). Productivity impacts of the system of rice intensification (SRI): A case study in West Bengal, India. Agricultural water management 87(1): 55 -60.

Stockle, S. (2016), Socioeconomic and Institutional Factors Influencing Adoption of Conservation Farming by Vulnerable Households in Zimbabwe, Agricultural Systems, Vol.101, No.1-2, Pp.20-29.

Tobin, T.P. (2016). Productive Water Use in Rice Production: Opportunities and Limitations. *Journal of Crop Production,* 2(2): 241-264.

URT (2017). Population Distribution in Tanzania. Government Press, Dar-es-salaam, Tanzania. 80 pp.

Weir, S. (2014). The Effects of Education on Farmer Productivity in Rural Ethiopia. Working Paper No. 7. Centre for the Study of African Economies, University of Oxford, UK.117pp.

WFP (2013). Value Chain Analysis of Rice and Rice in Selected Districts in Tanzania: Report. Dar es Salaam: Agricultural Council of Tanzania/Tanzania Agricultural Partnership. 20pp.

WFP (2016). Comprehensive Food Security and Vulnerability Analysis Tanzania. [http://vam.wfp.org,] site visited on 20/07/2011.

Wichelns D. (2013). Policy Recommendations to Enhance Farm-Level Use of Fertilizer and Irrigation Water in Sub-Saharan Africa. *The Journal Sustainable Agriculture,* 23(2): 53-77.

Yao R.T, Shively G.E. (2017). Technical Change and Productive Efficiency: Irrigated Rice in the Philippines. *The Asian Econ. J.* 21(2): 155-168.

Yap, C.L. (2016). A comparison of the Cost of Producing Rice in Selected Countries. Economic and Social Development Paper No. 101, FAO, Rome. 230pp

Zilberman D. (2015), Adoption of Agricultural Innovations in Developing Countries: A Survey, Economic Development and Cultural Change; 33(2):255–298.