International Journal of Statistics and Applied Mathematics

ISSN: 2456-1452
Maths 2022; 7(5): 83-93

www.mathsjournal.com
Received: 03-06-2022
Accepted: 08-07-2022

Hamenya Kasase
[1]Department of Population Studies, Institute of Rural Development Planning, P.O Box 138, Dodoma, Tanzania
[2]Department of Graduate Studies, Eastern Africa Statistical Training Center, P.O Box 35103, Dar es Salaam-Tanzania

Boniphace Shija NOBEJI
Department of Graduate Studies, Eastern Africa Statistical Training Center, P.O Box 35103, Dar es Salaam-Tanzania

Saxena Kuldeep Kumar
Department of Statistics, University of Dodoma, Dodoma-Tanzania

Rajabu Joseph Kangile
Tanzania Agricultural Research Institute (TARI) – Dakawa Centre, P. O. Box 1892, Morogoro – Tanzania

Corresponding Author:
Hamenya Kasase
[1]Department of Population Studies, Institute of Rural Development Planning, P.O Box 138, Dodoma, Tanzania
[2]Department of Graduate Studies, Eastern Africa Statistical Training Center, P.O Box 35103, Dar es Salaam-Tanzania

Measuring the intensity of adoption of the system of rice intensification and improved rice seeds technologies in Geita district, Tanzania: An application of the adoption quotient and the double hurdle model approaches

Hamenya Kasase, Boniphace Shija NOBEJI, Saxena Kuldeep Kumar and Joseph Rajabu Kangile

DOI: https://doi.org/10.22271/maths.2022.v7.i5b.884

Abstract
The System of Rice Intensification (SRI) and Improved Rice (IRS) technologies are increasingly being disseminated to rice farmers in Tanzania to boost rice production [1, 2]. The use of these technologies is considered as an important milestone in improving rice productivity in the Country. However there remains a challenge in assessing and measuring the adoption of such technologies by farmers and their associated determinants. This study sought to apply the adoption quotient to assess the intensity of adoption of SRI and IRS technologies and examine the effects of institutional factors on the intensity of adoption using the double hurdle model. Data were collected using a structured questionnaire administered to 324 rice farmers from Nyamwilolelwa ward in Geita District, Tanzania, during the 2020 crop season. The research used cross-sectional survey method conducted and the questionnaire were administered using ODK – Kobo Collect technology. Data analysis for both, descriptive and inferential statistics was done on Stata version 14. The results from the adoption quotients estimates revealed a low adoption of SRI and IRS technologies whereby only 37.96% of rice farmers in the study area were found to have adopted the principles of SRI and IRS technologies, whereby on average the farmers adopted only 23.74% of the elements of SRI and IRS technologies. Results from the first hurdle regressions revealed that, extension visit, agriculture support, and the type of farming system, are significant in predicting the probability of adopting SRI and IRS technologies ($p<0.05$). With regard to the intensity of adoption, results from the second hurdle regressions revealed that extension consultation, distance to a nearby cooperative member, and experience in water management difficulty, are significant in predicting the intensity of adoption ($p<0.05$). The main conclusions drawn from this study is that the decision to adopt or dis-adopt SRI and IRS technologies is significantly determined by training, extension consultation, agriculture support and type of farming system. We furthermore conclude that the intensity of adoption of SRI and IRS technologies is significantly determined by extension consultation, distance to a nearby cooperative member, and water management difficulty. The study recommends improving and strengthening extension services, training and dissemination programs in order to increase the uptake of innovated rice technologies.

Keywords: System of rice intensification, improved rice seeds, technology, adoption

Introduction
Rice is one of the world's three most important grain crops, with major contribution to food security across the global, which is grown in almost all continents except the Antarctica [3, 4]. The global consumption of rice in 2021/2022 crop year was about 509.87 million metric tons, which is up from 437.18 million metric tons in the 2008/2009 crop year, with China being the World's top producer, India and China accounting for the largest harvested area, India being the top world exporter and China the top importer of rice in the world [5].

High production in the world's leading countries is largely contributed by high level of technology in rice production which is highly adopted by large scale producers. In Africa, production and consumption of rice is on the rapid increase. The Western Africa accounts for almost 40 percent of all rice produced in Africa while Egypt, Madagascar and Nigeria, are the individual countries with the largest production in the continent [6]. However, quantities of rice produced in Africa is due to increase of area under rice cultivation and is not sufficient, therefore the balance is met by the quantities imported from outside. The share of Africa is only 3 percent of global production of rice [7].

In Eastern Africa, rice production is largely contributed by Tanzania and Uganda, Tanzania being the largest exporter of rice to the East Africa Community market. On the other hand, Kenya accounts for the largest import of rice in the EAC region. On the aspect of self-sufficiency, all countries of EAC are not self-sufficient, with Kenya being the least sufficient and Tanzania being the most sufficient (over 90% sufficient). On the aspect of yield, Kenya whose production is largely irrigation, has the highest yield (4.7 MT/Ha) compared to that of the region (3.2 MT/Ha) [8].

In Tanzania, rice is grown in many parts of the country, and is one of the three important food and widely grown crops both main land and Zanzibar, following after maize and cassava. Production of rice in Tanzania has a fluctuating pattern due to seasonal effects. Rice is the second dominant crop in Tanzania, following after maize [9]. Total area planted with paddy is approximately around 1.5 million hectares with more than 1.5 million operators [9, 10]. Increase in production in Tanzania is not due to increased production efficiency, that is, not per unit production, but rather it is a result of increase in the area under rice cultivation. Rice yield in Tanzania - stands at 1.5 t/ha which is even far below that of African region which stands at 2.5 t/ha [11]. More than 90 percent of the area under rice cultivation is characterized by small-holder subsistence farming [1].

The use of improved rice technologies is an important milestone in improving rice productivity, water resilience, and land management in Tanzania. However, the adoption of improved rice technologies remains low despite the increasing technology inventions and extensive disseminations being done in Tanzania. Uptake of water management techniques, use of improved rice varieties, application of fertilizers, uptake of improved planting and cultivation techniques as well as pest and disease management technologies still remain low. This is a prevailing challenge which is observable in almost all rice producing zones in Tanzania. As a result, rice yield in the country has continuously remained below the potential level. Researchers addressing this problem have not reached to a consensus as to what determines the adoption of improved rice technologies by farmers as there seems to be a wide spectrum of factors, with varying influence depending on the agro-ecological context. Addressing this problem would require micro-studies on particular agro-ecological site in order to reveal factors that determine technologies adoption, which are specific to a particular area and examining the effects of adoption intensity on rice production. This study sought to apply the adoption quotient to assess the intensity of adoption of SRI and IRS technologies and examine the effects of institutional factors on the intensity of adoption using the double hurdle model.

Materials and Methods

Research Design

A cross-sectional quantitative research approach was used to examine the determinants of SRI and IRS technology adoption. The researcher resorted to adopt cross-sectional survey approach in order to allow the examining of the variation of technology adoption between different cases, i.e., key project participants and non-participants, and the examining of associations between variables [12]. Moreover, cross-sectional design necessitates the examining of causal relationship between variables and hence allows the drawing of causal inference from the research (Ibid).

Target population

This study targeted smallholder farmers who engage in rice production in Geita district, Geita region. Three villages from Nyamwilolelwa ward were involved in the study which are: Nungwe, Saragurwa, and Nyamwilolelwa respectively. This population was selected purposefully because it is where the SRI and IRS technologies have been promoted for a couple of years. The system of rice intensification and the improved rice seeds technologies were both introduced and disseminated in this ward and it is thus anticipated to have been the model of good agricultural practices (GAPS) in Geita District as far as rice production is concerned.

Sampling strategies

The sample frame constituted all adults who engage in rice production in the three villages, regardless of where they currently reside. The study used individuals as unit of samples. The study used probability sampling technique by employing a mix of stratified random sampling and simple random sampling procedure. The main criteria for stratification based on the farmer's project membership status whereby two strata were formed basing on this criterion. From each stratum, simple random sampling procedure was used to select samples for inclusion in the study. The technique involves identification and listing rice farmers in the study area and thereafter, a random sampling procedure was used to pick a farmer from the established list. Since the variance of the strata is not known, therefore allocation of sample units to the two strata followed proportional allocation method. The sampling technique explained was chosen because of its strength in allowing equal chance among individuals to participate in the study and reduction of sampling error, which therefore minimizes sampling bias and increase statistical inference power. The study used primary data which were collected directly from rice farmers in the study area using semi-structured questionnaire. Computer-Assisted Personal Interviewing technology (CAPI) using Kobo Collect Application was used to transfer the survey questionnaire into android devices for use by the enumerators in data collection. The researcher recruited enumerators to assist in data collection.

This study assumes a maximum variability in SRI and IRS technology adoption to be 50% (0.5). A sample of 384 rice farmers computed by using the proportion formular proposed by Cochran (1963) as

$$n = \frac{Z^2.p.q}{e^2} \qquad [1]$$

Measurement of Adoption

Adoption is a variable which takes two stages whereby, at first stage is binary outcome and at the second stage it takes a continuous form indicating the level or intensity of adoption. Various approaches have been proposed for measuring the adoption intensity, such as using adoption index as proposed by [13] and cited by [14], and using adoption quotient as proposed by [15]. However, quotient formula developed by [15] as used in several adoption studies such as [16, 17] has been found to provide results which are valid enough to measure the adoption behaviour of farmers. This study therefore adapts the quotient approach compute the weighted intensity of adoption of SRI and IRS. We first calculated the unweighted adoption quotients for each of the two technologies, i.e., SRI and IRS, and then applied the weighing in order to smooth the scores. The weights for each of the two technologies were derived from the principal components whereby for SRI the weight was 0.7448 and for IRS technology it was 0.2552. Quotient scores were computed for each respondent based on the identified elements of the SRI and IRS technologies package. Assuming that the extent of adoption varies over time but the potential adoption remains constant, the adoption quotient of an individual rice farmer was computed using the customized equation 2;

$$AQ = \frac{\sum_{j=1}^{N}\left(\frac{\sum_{t_p-t_1}^{i=1} e_j}{(t_p-t_1)P_j}\times W_j\right)}{\sum_{j=1}^{N} W_j}\times 100 \qquad [2]$$

Where; AQ is the adoption quotient e_j is the extent of adoption of any particular practice in a particular year t_p is the time of investigation (year); t_1 is time of first introduction of the jth practice in the village/ward (year), for some farmers, this indicated the time farmers begun rice farming at the first time with the time scope of the study; P_j is the potential of any particular (jth) practice from which e_j is calculated in that particular year; W_j is the weight to be given to a particular (jth) practice based on its difficulty of adoption determined from a list of differential weights of practice $\sum_{j=1}^{N} is$ the summation over each of the N practice; $\sum_{t_p-t_1}^{i=1} is$ the summation over each year from $t_1\ to\ t_p$.

Definitions and measurements of explanatory variables

The explanatory variables used in this study were the institutional variables which are defined and measure as shown in Table 1.

Table 1: Definition and Measurement of variables

Definition of variables	Nature and units of measurement of variables	Expected Sign
Dependent variables		
Adoption	Dummy (1=Yes; 1=No)	
Intensity of adoption	Continuous (Adoption Quotient)	
Independent variables		
Institutional variables		
Received agric. Training:	Dummy (1=Yes; 0=No)	Positive (+)
Had contact with ext. agent:	Dummy (1=Yes; 0=No)	Positive (+)
Distance Input source:	Dummy (1=0-1Km; 0=Otherwise)	Negative (-)
Distance to a cooperative member:	Dummy (1=0-1Km; 0=Otherwise)	Negative (-)
Received any in-kind support:	Dummy (1=Yes; 0=No)	Positive (+)
Water management difficulty:	Dummy (1=Yes; 0=No)	Negative (-)
Type of farming system:	Dummy (1=Rainfed, 0=Otherwise)	

Cragg's double-hurdle model (DHM)

The Cragg's double hurdle model is an extension and improvement over the limitations of the Tobit model. Despite the fact that Tobit model has gained popularity in modelling limited dependent variables, there are several limitations which makes it ineffective in particular studies. One of the drawbacks of the Tobit model is that it assumes that the same set of explanatory variables determines both the probability and the extent of adoption, thereby truncating the data at positive values. As a result, especially in micro-studies, the number of observations is reduced due to parameterization effect which cause the data to be non-robust, which affects predictive power of the model. Heckman proposed a two-stage model in order to include the zero-observation in the model and it has turned out to be relatively convincing. However, in non-normality and heteroskedastic situations, the hackman model has been found to be even less efficient as compared to the Tobit. Cragg developed the alternative double hurdle model which is flexible and can accommodate the non-normality and heteroskedasticity situation. The most important assumption of the Cragg's model is that the factors explaining the probability of adoption are not necessarily the same as those explaining the extent (intensity) of adoption. The model proposes that an individual has to cross two hurdles to complete the adoption process. The first hurdle involves the decision to either adopt or dis-adopt. If the first hurdle is crossed, then the net hurdle is the decision as to how much to adopt. For example, at the beginning of crop season, a farmer can decide to adopt the SRI and IRS technologies, but as the first decision is made, prices of inputs may rise and impede the decision of adoption intensity, whereby the farmer may be found to have zero values in adoption intensity. Therefore, from this basis and with respect to the nature of this study, I use the Cragg's model to analyze the factors determining the probability of adopting SRI and IRS technologies. The model is specified using two hurdles: the first being the probit hurdle, for modelling the probability of adopting; and the other one is the truncated hurdle nested into the Tobit, as shown below in equation 3 below;

$$d_i^* = Z_i\alpha + v_i;\ v_i \sim \mathrm{N}(0,1);\ i=1, 2, 3, \ldots n \qquad [3]$$

$$d_i = \begin{cases} 1, if\ d_i^* > 0 \\ 0, if\ d_i^* \leq 0 \end{cases}$$

$$y_i^* = x_i\beta + \varepsilon_i;\ \varepsilon_i \sim \mathrm{N}(0, \sigma\ 2);\ i=1, 2, 3, \ldots n \qquad [4]$$

$$y_i = \begin{cases} x_i\beta + \varepsilon_i, if\ x_i\beta + \varepsilon_i > 0\ and\ Z_i\alpha + v_i > 0 \\ 0\ otherwise \end{cases}$$

Where d_i^* is the latent variable describing farmer's decision to adopt, which in this case it represents the first hurdle, y_i^* is the latent variable describing the farmer's decision on the level of adoption. y_i is the observed adoption quotient representing the intensity of adoption of SRI and IRS technologies, z_i is a vector of variables explaining whether a farmer adopts SRI and IRS technologies, x_i is a vector of variables explaining the extent (intensity) of adoption measured as adoption quotient, v_i and ε_i are the error terms, assumed to be independent with distribution: $v_i \sim \mathrm{N}(0,1)$ and $\varepsilon_i \sim \mathrm{N}(0, \sigma\ 2)$. α and β are the unobserved parameters (coefficients) to be estimated.

The standard DHM is estimated by using the Maximum Likelihood Estimation (MLE) technique, thereby maximizing the log likelihood (LL) function as given in equation 5 below;

$$LL_{DHM} = \sum_0 ln\left[1-\Phi(Z_i\alpha)\Phi\left(\frac{\chi_i\beta}{\sigma_i}\right)\right]+\sum_+ ln\left[\Phi(Z_i\alpha)\frac{1}{\sigma_i}\phi\left(\frac{y_i-\chi_i}{\sigma_i}\right)\right] \quad [5]$$

Here, Φ and ϕ represent probability density function (PDF) of the probability regression and cumulative density function (CDF) of the truncated regression.

Estimation of marginal effects of the adoption determinants

The marginal effects which were calculated using the MLE results obtained from the DHM, were used to assess the impact of regressors on the outcome variable. This was done by decomposing the unconditional expectation into two components: the conditional expectation $\mathrm{E}[y_i|x, y_i > 0\,]$, i.e., the expected value of y_i (adoption quotient) for values of explanatory variables x, conditional of $y_i > 0$; and the probability of positive values (non-zero outcome) of y_i (adopt) for the values of the explanatory variables, x, $\mathrm{P}[y_i > 0|x\,]$.

The probability of adoption expressed by equation 6;

$$\mathrm{P}[y_i > 0|x] = \Phi(Z_i\alpha)\Phi\left(\frac{x_i\beta}{\sigma_i}\right) \quad [6]$$

The expected intensity of adoption (adoption quotient) conditional on adoption is expressed using equation 7;

$$\mathrm{E}[y_i|x, y_i > 0] = \Phi\left(\frac{x_i\beta}{\sigma_i}\right)^{-1}\int_0^\infty\left[y_i\frac{1}{\sigma_i}\phi\left(\frac{y_i(\Theta)-x_i\beta}{\sigma_i}\right)(1+\Theta^2{y_i}^2)^{-\frac{1}{2}}\right]dy_i \quad [7]$$

The unconditional mean which is used to measure the overall average adoption intensity, measured by the AQ is expressed as shown in equation 8;

$$\mathrm{E}[y_i|x] = \mathrm{P}[y_i > 0|x]\,\mathrm{E}[y_i|x, y_i > 0] \quad [8]$$

The marginal effects were derived by differentiating the three equations (9, 10 and 11) with respect to each explanatory variable, using numerical integration and differentiation methods as;

$$\frac{\partial \mathrm{P}[y_i>0|x]}{\partial x_j} = \alpha_j\phi(Z_i\alpha)\Phi\left(\frac{x_i\beta}{\sigma_i}\right)+\beta_j\Phi(Z_i\alpha)\phi\left(\frac{x_i\beta}{\sigma_i}\right) \quad [9]$$

Marginal effects of conditional mean of AQ were derived as;

$$\frac{\partial \mathrm{E}[y_i|x,y_i>0]}{\partial x_j} = \beta_j-\beta_j\left[\frac{\phi\left(\frac{x_i\beta}{\sigma_i}\right)}{\Phi\left(\frac{x_i\beta}{\sigma_i}\right)}\right]\times\left[\frac{x_i\beta}{\sigma_i}+\left(\frac{\phi\left(\frac{x_i\beta}{\sigma_i}\right)}{\Phi\left(\frac{x_i\beta}{\sigma_i}\right)}\right)\right] \quad [10]$$

The marginal effect for the unconditional adoption quotient was then derived using the product rule of differentiation as follows:

$$\frac{\partial \mathrm{E}[y_i|x]}{\partial x_j} = \frac{\partial \mathrm{P}[y_i>0|x]}{\partial x_j}\times \mathrm{E}[y_i|x,y_i>0]+\frac{\partial \mathrm{E}[y_i|x,y_i>0]}{\partial x_j}\times \mathrm{P}[y_i>0|x]$$

In the above equations, α_j and β_j are the coefficients on the explanatory variable x_j form the adoption and AQ equations respectively.

The standard errors of the estimated elasticities were computed using equation 12;

$$\mathrm{var}(e) = \left[\frac{\partial h(\widehat{T})}{\partial(\widehat{T})}\right]\Sigma\left[\frac{\partial h(\widehat{T})}{\partial(\widehat{T})}\right] \quad [12]$$

Where

$\widehat{T}$ is ML estimator of all parameters $T = [\propto, \beta, \Theta, \mathrm{W}]$; Σ is the variance-covariance matrix; $h(\widehat{T})$ is a specific elasticity (a scalar), denoted as e.

Results and Discussion

Socio-demographic characteristics of respondents

Data on socio-demographic characteristics i.e., age, gender, marital status, income level, and education were collected, (Table 2). Overall, the study comprised of 213(65.74%) and 111(34.26%) with mean age and range of 43.08(20-76) and 39(20-68) for males and females respectively. This implies that there more males engaging in rice farming as compared to their female counterparts. It is furthermore deduced from these findings that rice farming in the study area is dominantly done by adults with minimal gender variation in terms of age range of rice farmers.

Table 2: Demographic Characteristics of respondents

Variable	Male		Female		Total Sample	
Continuous variables						
Mean age in years (range)	43.08(20-76)	-	39.05(20-68)	-	-	-
Categorical variables:	**n/N**	**%**	**n/N**	**%**	**n/N**	**%**
Gender	213/324	65.74	111/324	34.26	324/324	100
Farmer's Marital Status						
Married	194/213	91.08	83/111	74.77	277/324	85.49
Never married	12/213	5.63	4/111	3.60	16/324	4.94
Widowed	3/213	1.41	7/111	6.31	10/324	3.09
Divorced	2/213	0.94	8/111	7.21	10/324	3.09
Separated	2/213	0.94	9/111	8.11	11/324	3.40
Education level						
No formal school	53/213	24.88	38/111	34.23	91/324	28.09
Primary school	145/213	68.08	69/111	62.16	214/324	66.05
O-Level secondary	14/213	6.57	4/111	3.60	18/324	5.56
College Diploma	1/213	0.47	0/111	0.00	1/324	0.31

***Source*:** Researcher's own computations from field data, 2020

Regarding respondent's marital status, majority of respondents i.e., 277(85.49%) are married, implying that rice farming is predominantly done by married farmers. The rest 16(4.94%), 10(3.09%), 10(3.09%) and 11(3.40%) comprises of never married, widowed, divorced and separated individuals respectively. It is furthermore deduced that there are just minimal sex differentials in terms of marital status of respondents, which implies that male and female rice farmers are similar to each other in terms of marital status, with just minor differences.

On education aspect, majority of respondents, i.e., 214(66.05%) attained primary school as their highest level of education. It is also found that nearly one third, i.e., 91(28.09%) of respondents have no formal education. There were only few respondents who attained secondary education level, and college whereby only 18(5.56%) and 1(0.31%) reported to have attained O-level secondary and college diploma education level.

Furthermore, examining sex differentials in terms of education level, results show that there is a larger proportion of males who attained primary school level (68.08%) as compared to their female counterparts (62.16%), and larger proportion of females who have no formal education (34.23%) than males (24.88%).

Results from descriptive analysis

Table 3 and Figure 1 shows the percent of adopters and non-adopters and the mean and range of adoption of SRI and IRS technologies in the study area. It was revealed that majority of rice farmers have adopted at least one element of the SRI and IRS technologies as indicated by 82.19 of adopters. However, it was furthermore revealed that the rate of adopting the SRI and IRS technologies when taken separately ranges between 0-59 and 0-61, with means of 12.31 and 11.43 percent respectively. These results indicate that rice farmers in the study area adopt the two technologies concurrently and at almost same rate. This was furthermore confirmed by correlation test, whereby a Spearman's correlation was run to assess the relationship between the rate of adoption of SRI and that of IRS technologies. Correlation results showed a moderate positive correlation between rate of adoption of SRI and that of IRS technologies, which was statistically significant (rho = 0.3250, p = 0.0000).

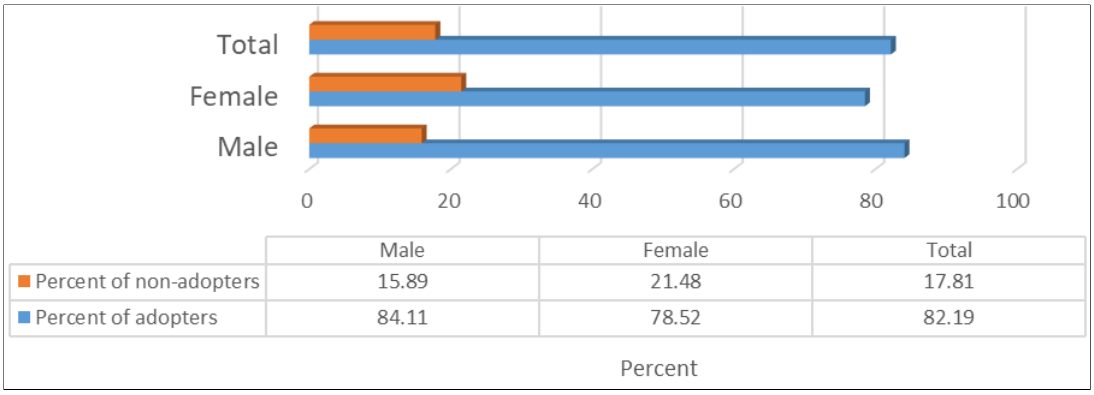


Fig 1: Adoption rate by Sex

These results justify the reason for studying the two technologies together in order to account for their endogeneity and simultaneity nature, hence combining them using a composite adoption quotient as a proxy of adoption intensity was a better approach. The computed adoption quotient shows that the intensity of adoption of the two technologies taken together ranges between 0-100, with a mean of 23.74 percent respectively. Overall, the study found that only 37.96 had adopted the SRI and IRS technologies, indicating a low rate of adoption of the SRI and IRS technologies in the study area (Table 3 and 4). The field visits by the researchers on farmers' plots observed some of the farm fields planted for the next season which were found to implement only a few of the principles recommended in the SRI or using improved seeds in just small portions of their rice fields (Plate 1).

Table 3: Intensity of SRI and IRS Adoption

Adoption Intensity	Mean (Range)	CI 95%
SRI Adoption rate(range)	12.31(0-59)	0.110 - 0.137
IRS Adoption rate(range)	11.43(0-61)	0.097 - 0.131
Composite Adoption Quotient(range)	23.74(0-100)	21.368 - 26.120

Source: Researcher's own computations from field data, 2020

Source: Researcher's own photo caption during field survey, 2020

Plate 1: Young seedlings planted as recommended in SRI principles

Results from descriptive analysis presented in Table 4 indicated that, majority that is 106(97.25%) and 160(74.42%) of respondents who have and who had consulted with an extension agent for rice farming advice and service, have adopted the SRI and IRS. Regarding distance, of those respondents residing 0-1 Km, 1-5 Km and 5 Km or more, there were 79(83.16%), 117(75.97%) and 70(93.33%) respondents who reported to have adopted the SRI and IRS technologies. Also, regarding the distance to the farmer who is a cooperative member, respondents residing 0-1 Km, 1-5 Km and 5 Km or more, reported to have adopted the SRI and

IRS technologies. On the aspect of agriculture support, 76(97.44%) and 190(77.24%) from respondents who have and who have not received agriculture support reported to have adopted SRI or IRS technologies. With regard to whether the respondent experienced difficulty in controlling water in rice fields, 165(84.62%) and 101(78.29%) respondents who have and those who have not experienced the problem, have adopted the SRI and IRS technologies. Moreover, from the type of farming system, 244(80.79%) respondents who solely use rainfed system reported to have adopted SRI and IRS technologies. Results also show that all respondents who use irrigation and those using a mix of rainfed and irrigation, that is 5(100.00%) and 15(100.00%) respectively have adopted SRI and IRS technologies.

Table 4: Institutional and attitudinal variables by adoption status

Institutional Variables	Adopters:		Non-Adopters:		Total Sample		p-value
	n/N	%	n/N	%	n/N	%	
Agric. Training							
Yes	119/123	96.75	4/123	3.25	123/324	37.96	0.00
No	73/201	73.13	54/201	26.87	201/324	62.04	
Extension Consult							
Yes	106/109	97.25	3/109	2.75	109/324	33.64	0.00
No	160/215	74.42	55/215	25.58	215/324	66.36	
Distance to Input							
Km 0 -1	79/95	83.16	16/95	16.84	95/324	29.32	0.01
Km 1 - 5	117/154	75.97	37/154	24.03	154/324	47.53	
Km 5 +	70/75	93.33	5/75	6.67	75/324	23.15	
Distance to a cooperative member							
Km 0 -1	123/154	79.87	31/154	20.13	154/324	47.53	0.32
Km 1 - 5	139/164	84.76	25/164	15.24	164/324	50.62	
Km 5 +	4/6	66.67	2/6	33.33	6/324	1.85	
In-kind support							
Yes	76/78	97.44	2/78	2.56	246/324	75.93	0.00
No	190/246	77.24	56/246	22.76	78/324	24.07	
Water Overflow							
Yes	165/195	84.62	30/195	15.38	195/324	60.19	0.15
No	101/129	78.29	28/129	21.71	129/324	39.81	
Type of farming system							
Rainfed	244/302	80.79	58/302	19.21	302/324	93.21	0.08
Irrigation	5/5	100.00	0/5	0.00	5/324	1.54	
Mixed	17/17	100.00	0/17	0.00	17/324	5.25	

***Source*:** Researcher's own computations from field data, 2020

Results from Inferential Analysis

Tests for normality of residuals of the DHM model

The log likelihood presented in the DHM is based on the assumptions of homoskedasticity and normality of the error terms: v_i ~ N(0,1) and ε_i ~ N(0, σ^2). However, in such cases when either of these assumptions is violated, the MLE will likely produce inconsistent parameter estimates [18, 19]. There are different approaches to allow for non-normal errors, one of which is to use the transformation procedure whereby the outcome variable is transformed in order to accommodate the non-normal errors. Different procedures have been proposed such as the Box-Cox transformation and the Inverse Hyperbolic Sine (IHS) transformation. However, there are several drawbacks with the Box-Cox Transformation as pointed out by previous studies, such as its failure to guarantee that the transformed variables are strictly normal and its failure to transform negative values [18, 19]. In this regard therefore, the IHS is considered to be more effective [20], and we therefore used it in this study when non-normality was realized. The IHS is expressed as:

$$y_i(\Theta) = log\left[\Theta y_i + (\Theta^2 y_i^2 + 1)^{\frac{1}{2}}\right] = \sinh^{-1}(\Theta y_i)/\Theta \quad [16]$$

Where; Θ is unknown parameter which makes the transformation linear as it approaches zero. When the values of the outcome variable (y_i) are large, the transformation behaves logarithmically and it is thus suited for handling outliers. One of the key strengths of this transformation is that it is scale-invariant.

The test was implemented in order to test whether the residuals obey the key assumptions of the double hurdle model that residuals are normally distributed and compare which one between the normal DHM, homoscedastic IHS-DHM and heteroscedastic IHS-DHM is the best fit. Results from this test, which were used to select the model to implement are presented in Tables 5. These tests were important in order to assure that the model selected fits well and that there are no spurious results due to violation of model assumptions.

Table 5: Tests for normality of residuals of the Double Hurdle Models

Model	Variable	Obs.	Pr. (Skewness)	Remarks	Decision
Normal Homoscedastic DHM	Residual	324.00	0.00	Non-normal	Decline
IHS-DH Homoscedastic	Residual	324	0.50	Normal	Select
IHS-DHM adjusted for Heteroskedasticity	Residual	324	0.00	Normal	Decline

***Source*:** Researcher's own Stata computations from field data, 2020

The normality tests indicated that the homoscedastic model addresses the normality assumption better than the normal homoscedastic and the IHS model. Furthermore, the goodness-of-fit test to compare the alternative models and as model selection criteria was performed using Akaike's Information Criteria (AIC) and the Bayesian Information Criteria (BIC) This test was done in order to evaluate which of the three has more predictive power. Results of this fit test as presented in Table 6 lead to selecting the homoscedastic IHS-DH as the empirical model due to its lower BIC and AIC values indicating a better fit compared to its alternative model.

Table 6: Goodness of fit test by Akaike's Information Criteria

Model	df	AIC	BIC	Remarks	Decision
IHS-DH Homoscedastic Model	23	853.93	940.88	Best fit	Select
IHS-DH Model adjusted for Heteroskedasticity	29	871.28	980.93	Better fit	Decline

***Source*:** Researcher's own Stata computations from field data, 2020

After incorporating the IHS transformation, then the IHS-DHM was specified as:

$$y_i(\Theta) = \begin{cases} x_i\beta + \varepsilon_i, if\ x_i\beta + \varepsilon_i > 0\ and\ Z_i\alpha + v_i > 0 \\ 0\ otherwise \end{cases} \quad [17]$$

After the IHS transformation and observing the assumption of independency of error terms (v_i and ε_i), likelihood function of the independent sample was specified as:

$$L = \prod_{y_i=0}\left[1 - \Phi(Z_i\alpha)\Phi\left(\frac{x_i\beta}{\sigma_i}\right)\right]\prod_{y_i>0}\left[\Phi(Z_i\alpha)\frac{1}{\sigma_i}\phi\left(\frac{y_{i(\Theta)} - x_i\beta}{\sigma_i}\right)\left(1 + \Theta^2 y_i^2\right)^{-\frac{1}{2}}\right] \quad [18]$$

A solution for heteroskedasticity i.e., violation of homoskedasticity assumption, was to allow the standard deviation (σ_i) to vary across observations and specify it as a function of a set of exogeneous or continuous variables as;

$$\sigma_i = \exp(\mathrm{W}_i \mathrm{h}) \quad [19]$$

Where; W_i is a set of exogeneous variables and h is the parameter vector which can be estimated in a similar way like α, β and Θ using ML method.

Marginal effects of institutional factors on SRI and IRS adoption decision - First hurdle

Results from the marginal effects analysis in the first hurdle (the probability hurdle) showed that four variables were significant in the first hurdle. Interpretation for marginal effects of these variables as presented in Table 7 is presented in the proceeding sub-sections.

Table 7: Marginal effects of institutional determinants of adoption

Explanatory Variables	1st Hurdle (Probit, C. I=95%)			2nd Hurdle (Truncated, C. I=95%)		
	Marginal Effects	Std. errs.	p-value	Marginal Effects	Std. errs.	p-value
Agric. training						
No	-Ref-	-Ref-	-Ref-	-Ref-	-Ref-	-Ref-
Yes	0.74	0.23	0.00	0.19	0.14	0.19
Extension Consult						
No	-Ref-	-Ref-	-Ref-	-Ref-	-Ref-	-Ref-
Yes	0.63	0.25	0.01	0.28	0.14	0.04
Distance to Input						
Km 0 -1	-Ref-	-Ref-	-Ref-	-Ref-	-Ref-	-Ref-
Km 1 - 5	-0.36	0.2	0.08	-0.16	0.11	0.15
Km 5 +	0.34	0.23	0.14	-0.08	0.14	0.59
Distance to a coop. member						
Km 0 -1	-Ref-	-Ref-	-Ref-	-Ref-	-Ref-	-Ref-
Km 1 - 5	0.03	0.18	0.88	-0.29	0.11	0.01
Km 5 +	-0.16	0.70	0.82	0.49	0.37	0.19
In-kind support						
No	-Ref-	-Ref-	-Ref-	-Ref-	-Ref-	-Ref-
Yes	0.53	0.26	0.04	0.23	0.13	0.07
Water Mgt difficulty						
No	-Ref-	-Ref-	-Ref-	-Ref-	-Ref-	-Ref-
Yes	0.11	0.26	0.48	0.20	0.09	0.03
Type of farming system						
Rainfed	-Ref-	-Ref-	-Ref-	-Ref-	-Ref-	-Ref-
Irrigation	0.71	0.33	0.03	0.05	0.32	0.89
Mixed	0.70	0.20	0.00	0.04	0.18	0.83

***Source*:** Researcher's own Stata computations from field data, 2020

Participation in agricultural training

Results showed that participation in agricultural training has positive and statistically significant in predicting the probability of adopting SRI and IRS technologies (p=0.00, Sig at *p*<0.05), see Table 7. The null hypothesis that participation in agricultural training does not affect farmers' decision towards adoption of SRI and IRS technologies is therefore rejected. The predicted probability of adopting SRI and IRS was 0.74 greater for farmers who received agriculture training than for those who did not receive agriculture training. These results are consistent with the findings from previous studies such as [21-23] which also revealed that adoption decisions are affected by participation in extension-related variables such as training. The results imply that promoting and extending agriculture training to rice farmers would increase the uptake of the disseminated technologies by famers. It furthermore indicates that disseminating technologies to rice farmers and leaving them without providing any training would decrease the probability of its adoption. This points to the fact that training acts as a knowledge and skills transfer promotion mechanism through which farmers are introduced to the new technologies and encouraged to try the new technologies. The trainings act as the knowledge transfer whereby farmers are fed with knowledge and information on good agricultural practices and technologies.

Extension consultation

The effect of extension consultation through the visits made by extension agents and their contacts with rice farmers in the stud area was also ascertained in this study (Table 7). The predicted probability of adopting SRI and IRS was 0.63 greater for farmers who had some contacts and consultations with the extension personnel than for those who had not, and was statistically significant (p=0.01, Sig at $p<0.05$). This led to rejection of the null hypothesis that extension consultation does not affect farmers' decision towards adoption of SRI and IRS technologies. Similar results were found by [24] which posited that the decision to adopt improved rice varieties was significantly and positively influenced by extension visits. Another study by Hagos [25] found that rice farmers who had adopted upland rice technologies had better contacts with extension agents as compared to non-adopters. This points to the fact that extension contact or consultation often involves the following up and emphasis on the Good Agricultural Practices (GAPs) which promote the uptake of the disseminated technologies. Contact with extension agents enables rice farmers to close the gap of communication and hence allows farmers to access the technical advice from agents and motivation to try out and adopt newly disseminated technologies.

In-kind support

The predicted probability of adoption of SRI and IRS (Table 7) was 0.53 greater for farmers who have had received in-kind support than for farmers who had not, and was significant (p=0.04, Sig at $p<0.05$). The null hypothesis that agricultural support does not affect farmers' decision towards adoption of SRI and IRS technologies was rejected based on these results. Findings from focus group discussion of a similar study by [26] are similar to the findings of our study where it was reported that lack of institutional support constrained the adoption of improved rice varieties. This was ascertained from the present study, indicating that as farmers receive agricultural supports in form of inputs and material support, they are more likely to adopt the disseminated technologies as from the fact that the support facilitates the affordability of costs for executing the technologies. This is furthermore attributed by the fact that the introduction of the SRI and IRS technologies in the study area came with some form of in-kind supports such as distribution of fertilizers, rice seeds and irrigation water, which was free of charge. These supports were provided by Geita Gold Mining LTD during the commencing stage and progressed for few consecutive years. The findings from our study suggest that the ink-kind supports that came with the technologies in the study area motivated farmers to accept and take up the introduced technologies.

Type of farming system

The study revealed that the effect of type of farming system practiced by farmers is positive and statistically significant on predicting the probability of adopting SRI and IRS technologies (p=0.03, Sig at $p<0.05$), leading to the rejection of the null hypothesis that type of farming system does not affect farmers' decision towards adoption of SRI and IRS technologies (Table 7). The predicted probability of adopting SRI and IRS technologies was 0.70 greater for farmers using both rainfed and irrigation system, than for farmers who use rainfed system, and was statistically significant (p=0.00, Sig<0.05). These results are consistent with that reported by [26-28] which all found that irrigated farming systems have higher probability of adopting SRI and IRS technologies. This may be attributed to the fact that irrigated farming systems are endowed with sufficient water which is key to implementing the SRI technologies as well as using the improved rice seeds. Our study suggests that farmers who solely depend on rains in rice farming may not take up the SRI and IRS technologies. These findings are surprising because principally, the SRI and IRS are often thought friendly to water scarce farming because of its alternate drying and wetting which makes it possible to reduce water requirement. A study done in Cambodia by Lee [29] found similar results which reported water shortage as a constraint for adoption and adaption of SRI technology in rainfed lowland system.

Distance to the input source

Distance to the input source was not found to be statistically significant ($p>0.05$), hence the study failed to reject the null hypothesis that distance to the input source does not affect farmers' decision towards adoption of SRI and IRS technologies (Table 7). These results differ from the findings of past studies such as [22, 24, 30] which found that the distance that farmers travel to the nearest input source has significant influence on adoption of improved seeds varieties. This may be explained by the fact that majority of the rice farmers in the study area still practice organic farming due soil quality that is still conducive for organic farming and thus requiring little foreign input such as chemical fertilizers. Organic farming is well known for its low-input use characteristic hence requiring minimal contact with the input source. This might have led to insignificant effect of distance to the input source on decision towards adopting SRI and SRI technologies.

Distance to a cooperative member

Results from the study did not find statistically significant effect of distance to a cooperative member in the first hurdle ($p>0.05$), hence the null hypothesis that distance to a cooperative member does not affect farmers' decision towards adoption of SRI and IRS technologies could not be rejected (Table 7). Our findings differ from the past studies such as [24, 31]. This may have been attributed to the fact that the existing cooperative was formed during the same time when these technologies were disseminated, hence could not affect the adoption because it was not existing prior to the introduction of the technologies. This might also be explained by the fact which was obtained from the field that the established cooperative is not well established. This suggests that the spill-over effects may not be readily detectable at this stage.

Water management difficulty

The study found no statistically significant effect of water management difficulty on predicting the probability of adopting SRI and IRS technologies (p>0.05), hence the null hypothesis that water management determines the probability of adopting SRI and IRS could not be rejected (Table 7). Contrary to our findings, [26] reported that water management is a significant limiting factor to adopting SRI. The results suggest that decisions of rice famers as to whether to adopt or dis-adopt rice technology is dot dependent on their experience on difficulties in managing water that overflow in one's farm fields.

Effects of institutional factors on adoption intensity - Second hurdle

Results from the marginal effects analysis the second hurdle (truncated equation) shows three variables were significant. Interpretation for marginal effects of these variables follows in the proceeding sub-sections.

Extension consultation

The effect of extension visits on the intensity of adoption of SRI and IRS technologies was found to be positive and statistically significant ($p<0.05$), leading to the rejection of the null hypothesis that extension visits do not affect the intensity of adoption of SRI and IRS technologies (Table 7). The predicted adoption quotient is 0.28 greater for farmers who was visited by the extension officer than for farmers who did not. These results are similar to results reported by other studies such as [27, 28] which also found that adoption of SRI and IRS was constrained by inaccessibility to extension services. Extension visits act as catalysts of knowledge and skills transfer whereby the extension agents provide technical support and encouragement on the sustenance of the adoption.

Distance to a cooperative member

Results from the analysis show that the effect of distance to a cooperative member was negative and statistically significant in predicting the intensity of adoption of SRI and IRS technologies ($p<0.05$), leading to the rejection of the null hypothesis that distance to a cooperative member do not affect the intensity of adoption of SRI and IRS technologies (Table 7). The predicted adoption quotient is 0.29 less for famers whose residence distance to the nearby cooperative member is 1-5 Km, than for those whose residence distance is 0-1 Km. The effect of distance to a cooperative member were not found in the existing empirical literature, instead the past studies examined distance to the market and distance to the input sources [26-28], whereby it was similarly found that distance is a significant determinant of the intensity of adoption of SRI and IRS technologies. This is attributed to the fact that neighbouring with a cooperative member would facilitate the diffusion of innovation from one farmer to another and continuously act as a learning and sharing contact even in the absence of extension agents. This is due to the fact that cooperative members are likely to be equipped with essential techniques and skills of applying the principles of SRI and IRS technologies, and thus act as a learning centre for other farmers.

Water management difficulty

Results from this study indicate that water management difficulty was positive and statistically significant in predicting the intensity of adoption of SRI and IRS technologies ($p<0.05$), leading to the rejection of the null hypothesis that water management difficulty do not affect the intensity of adoption of SRI and IRS technologies (Table 7). The adoption quotient is 0.20 greater for farmers who experienced difficulty in managing water in their farm fields, than those who do not have that experience, and was statistically significant (p=0.03, Sig<0.05). These results are similar to that of [26, 32] but with opposite direction in that while the results from this study suggest experience in water management difficulties rises the predicted intensity of adoption, the past studies posited that experience in eater management difficulties lowers the intensity of adoption of SRI and IRS technologies, hence considered it as a constraint factor. From this study, the positivity of this variable may be attributed to the fact that majority of farmers who experienced water management difficulties were those whose rice fields are located along the water catchment and are thus endowed with sufficient water which in turn facilitates the implementation of SRI and IRS technology.

Participation in agricultural training

The results found that agriculture training, which was significant in the first hurdle of adoption, is no longer significant in the second hurdle ($p>0.05$). These results provide different observations from that of [10, 14] which indicated that participation in training would increase the intensity of adoption (Table 7). The different results from this study may be attributed to the fact that all trainings that were conducted with the rice farmers in the study area took place during the project initiation, and thus could only stimulate the decision to try and adopt the technologies, not the intensity. Hence, these results imply that when the decision to adopt was passed, the question of what extent to adopt did not depend on training.

Distance to input source

Similar to what was found in the first hurdle, also the results from the truncated model did not find statistically significant effect of distance to input source on the intensity of adoption of SRI and IRS technologies (p>0.05), hence the null hypothesis that distance to input source does not determine the adoption of SRI and IRS technologies could not be rejected (Table 7). These results disagree with results from past studies such as [24] which posited that distance to input source has significant influence on adoption of improved seeds varieties. As posited in the first hurdle, this was attributed to the fact that majority of the rice farmers in the study area practice organic farming due to the soil quality that is still conducive for organic farming and thus requiring little foreign input such as chemical fertilizers.

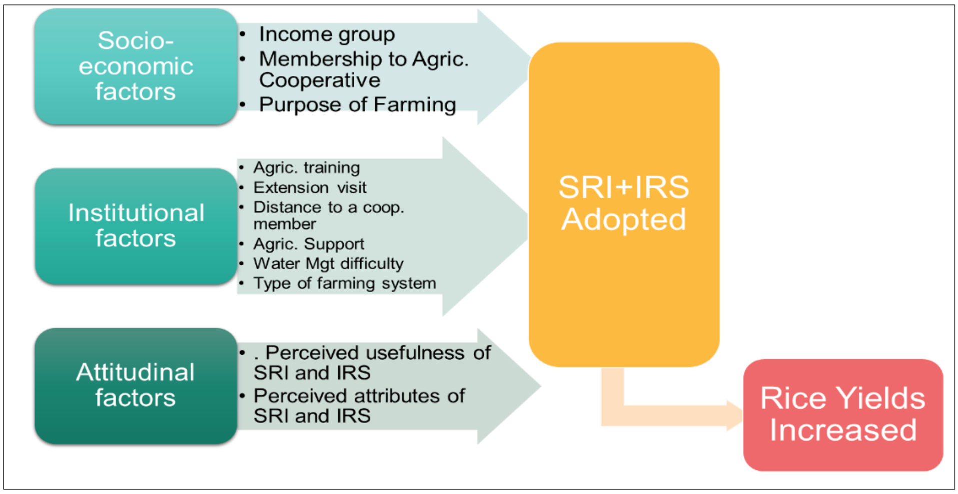
Agricultural support

Results from the truncated regression indicate that the effect of agricultural support is not statistically significant in predicting the intensity of adoption ($p>0.05$), hence the study could not reject the null hypothesis that agricultural support does not determine the intensity of adoption of SRI and IRS technologies in the study area (Table 7). This is different from the findings of Karki, (2011) which posited that agricultural support from the government and other stakeholders facilitates the adoption of SRI. These results are attributed to the fact that agricultural support that was provided was just meant for demonstration and stimulating the acceptance of the technologies by farmers during the dissemination and project initiation phase where after that phase, the support was stopped.

Type of farming system

Results from the truncated regression indicate that the type of farming system is not statistically significant in predicting the intensity of adoption of SRI and IRS technologies ($p>0.05$), hence the null hypothesis that type of farming system does not determine the intensity of adoption of SRI and IRS technologies in the study area could not be rejected (Table 7).

These results differ from that found by [34] which showed significant effect of irrigated farming on adoption SRI. This was attributed to the fact that the type of farming system in the study area was found to be almost identical in that majority practiced rainfed farming, which could not warrant a great variation.



Source: Researcher's Own Conceptualization drawn from the Research Findings, 2022

Fig 2: Revised Theory of Change

Conclusions

The main conclusions drawn from this study is that the decision to adopt or dis-adopt SRI and IRS technologies is significantly determined by training, extension consultation, agriculture support and type of farming system (Figure 2). We furthermore conclude that the intensity of adoption of SRI and IRS technologies is significantly determined by extension consultation, distance to a nearby cooperative member, and water management difficulty. The study recommends improving and strengthening extension services, training and dissemination programs in order to increase the uptake of innovated rice technologies.

Declarations

Acknowledgements

The author of this research acknowledges the financial support offered by the scale WAYS project from the International Institute for Applied Systems Analysis (IIASA).

Funding source

This research study received a research fund from the International Institute for Applied Systems Analysis (IIASA) under the "Scale WAYS" project.
Schlos splatz 1 - A-2361 Laxenburg, Austria;
TEL.: +43 2236 807 594;
Website: www.iiasa.ac.at

Competing Interests

The authors have no conflicts of interest.

References

1. Nkuba J, *et al.*, Rice value chain analysis in Tanzania: identification of constraints, opportunities and upgrading strategies, African Crop Science Journal. J. 2016;24(1):73-87.
2. Tenge A, Ley G, Hella J, Kinyau M, Opio F, Rwomushana I. Options to increase adoption of lowland rice-legume Technologies in Morogoro, Tanzania; c2013.
3. Chauhan BS, Jabran K, Mahajan G. Rice production worldwide, Springer; c2017, 247.
4. Muthayya S, Sugimoto JD, Montgomery S, Maberly GF. An overview of global rice production, supply, trade, and consumption, Annals of the new york Academy of Sciences. 2014;1324(1):7-14.
5. Shahbandeh M. Total global rice consumption 2008/09-2021/22, Statista, Jan. 2022 [Online]. Available: https://www.statista.com/statistics/255977/total-global-rice-consumption/. [Accessed: Feb. 25, 2022]
6. Maclean J, Hardy B, Hettel G, Rice Almanac: Source book for one of the most important economic activities on earth. IRRI; c2013.
7. MK Van Ittersum *et al.*, Can sub-Saharan Africa feed itself?, Proceedings of the National Academy of Sciences. 2016;113(52):14964-14969.
8. Kilimo Trust. Characteristics of Rice Markets in the EAC: Regional East African Community Trade in Staples (REACTS), Kilimo Trust, IFAD, Statistical; c2017.
9. NBS. 2014/15 Annual Agricultural Sample Survey (Crops and Livestock Report)," National Bureau of Statistics, Survey report; c2016.
10. NBS. 2016/17 Annual Agriculture Sample Survey. Crop and Livestock Report [Annual Report].," National Bureau of Statistics (NBS), Dar es Salaam,Tanzania, Survey Report; c2018.
11. Wilson RT, Lewis I. The rice value chain in Tanzania, A Report from the Southern Highlands Food Systems Programme, FAO; c2015, 9.
12. Becker S, Bryman A, Ferguson H, Understanding research for social policy and social work 2E: themes, methods and approaches. policy press; c2012.
13. Tiamiyu S, Akintola J, Rahji M. Technology adoption and productivity difference among growers of new rice for Africa in Savanna Zone of Nigeria, *Tropicultura*. 2009;27(4):193-197.
14. Obisesan A. Gender differences in technology adoption and welfare impact among Nigerian farming households; c2014.
15. Pareek U, Chattopadhyay S. Adoption quotient: A measure of multipractice adoption behaviour, The Journal of Applied Behavioral Science. 1966;2(1):95-108.
16. Hadiya B, Deshmukh G, Bariya M. Adoption of recommended practices of kharif groundnut growers in Saurashtra zone of Gujarat, Indian Research Journal of Extension Education. 2016;14(3):47-50.

17. Farid K, Tanny N, Sarma P. Factors affecting adoption of improved farm practices by the farmers of Northern Bangladesh, Journal of the Bangladesh Agricultural University. 2015;13(452-2016-35870):291-298.
18. Jiménez-Martín S, Prieto CV. Informal Care and intergenerational transfers in European Countriesℵ, Documento de Trabajo; c2013. p. 25.
19. Engel C, Moffatt PG. dhreg, xtdhreg, and bootdhreg: Commands to implement double-hurdle regression, The Stata Journal. 2014;14(4):778-797.
20. Hagger MS. The reasoned action approach and the theories of reasoned action and planned behavior; c2019.
21. Kumar A, *et al.*, Adoption and diffusion of improved technologies and production practices in agriculture: Insights from a donor-led intervention in Nepal, Land Use Policy. 2020;95:104621.
22. Suvedi M, Ghimire R, Kaplowitz M. Farmers' participation in extension programs and technology adoption in rural Nepal: a logistic regression analysis, The Journal of Agricultural Education and Extension. 2017;23(4):351-371.
23. Liu Y, Ruiz-Menjivar J, Zhang L, Zhang J, Swisher ME. Technical training and rice farmers' adoption of low-carbon management practices: the case of soil testing and formulated fertilization technologies in Hubei, China, Journal of Cleaner Production. 2019;226:454-462.
24. Abegunde V, Sibanda M, Osanyinlusi O. Adoption intensity of improved rice varieties in Ekiti state, Nigeria: a double hurdle approach, International Journal; c2018, 74(6/1).
25. Hagos H, Ndemo E, Yosuf. Factors affecting adoption of upland rice in Tselemti district, northern Ethiopia, Agriculture & Food Security. 2018;7(1):1-9.
26. Karki S. System of rice intensification: an analysis of adoption and potential environmental benefits; c2011.
27. Awotide B, Diagne A, Wiredu A, Ojehomon V. Wealth status and agricultural technology adoption among smallholder rice farmers in Nigeria, OIDA International Journal of Sustainable Development. 2012;5(2):97-108.
28. Varma P. Agricultural technology adoption under multiple constraints: an analysis of system of rice intensification (SRI) in India; c2016.
29. Lee YH, Kobayashi K. Assessing the acceptance of the system of rice intensification among farmers in rainfed lowland rice region of Cambodia, Paddy and Water Environment. 2018;16(3):533-541.
30. Krishnan P, Patnam M. Neighbors and extension agents in Ethiopia: Who matters more for technology adoption? American Journal of Agricultural Economics. 2014;96(1):308-327.
31. Asfaw S, Di Battista F, Lipper L. Agricultural technology adoption under climate change in the Sahel: Micro-evidence from Niger, Journal of African Economies. 2016;25(5):637-669.
32. Haldar S, Honnaiah T, Govindaraj GN. System of Rice Intensification (SRI) method of rice cultivation in West Bengal (India): An economic analysis; c2012.
33. Karki S. System of Rice Intensification: An analysis of adoption and potential environmental benefits; c2011.
34. Awotide BA, Karimov AA, Diagne A. Agricultural technology adoption, commercialization and smallholder rice farmers' welfare in rural Nigeria, Agricultural and Food Economics. 2016;4(1):1-24.