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Factors Affecting the Adoption of Stress-Tolerant Rice Varieties: Evidence from Bangladesh

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Climate change, through exposure to submergence, salinity, and droughts, affects crop production and leads to food insecurity, particularly in developing countries. Various climate-stress–tolerant rice varieties have been developed in many countries in the world to mitigate climate-related production losses. Despite the benefits of stress-tolerant rice varieties (STRVs), adoption rates are still low. This paper uses panel data from Bangladesh to analyse the factors influencing the adoption of STRVs. A random-effects probit model with the Mundlak approach is used to control for the farmer- and plot-level heterogeneities and to avoid the incidental parameters problem. The study finds that smallholder farmers are more inclined to adopt STRVs, proving that this technology is related to a type of adaptation in the form of adoption. The main drivers for adopting STRVs are information and knowledge transferred by extension workers, sharing knowledge by membership in an organisation, and learning from peers. Policy measures such as providing capacity enhancement activities, strengthening social capacity and local institutions, and implementing a site-specific policy are suggested to encourage the adoption of STRVs in climate-stress-prone areas.

Keywords: Technology Adoption, Submergence-tolerant Rice Varieties, Salinity-tolerant Rice Varieties, Climate Change, Panel Data, Bangladesh

JEL Classification: C33, O13, Q12, Q16

I. INTRODUCTION

Increasing agricultural production is crucial for global food security (Fuglie, 2021). However, climate change adversely affects agricultural productivity through exposure to weather events and climate disasters (IPCC, 2007; Almaraz, Mabood, Zhou, Gregorich, & Smith, 2008; Nelson et al., 2009; Ortiz-Bobea, Ault, Carrillo, Chambers, & Lobell, 2021). Consequently, its negative impact has led to the incidence of high poverty and food insecurity worldwide (Das, 2005; Nelson et al., 2009; Misra, 2012; Zaidi et al., 2018; Corwin, 2020).

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Bangladesh is among the countries that are most vulnerable to climate change, which poses a long-term threat to the country's agricultural sector, particularly in areas affected by flooding, saline intrusion, and drought (World Bank, 2016). Flooding is the most common climatic event and primary stress environment in Bangladesh. On average, out of a total area of 14.8 million hectares, about 1 million hectares of agricultural land are highly affected, and 5 million hectares are moderately affected by floods (Biswas, 2015). Flash floods regularly affect more than 18 districts in the country with varying degrees of severity. Another challenge in recent times is salinity intrusion, which affects agricultural production in the coastal regions (Alam et al., 2017; Halima, Azzouzi, Douaik, Azim, & Zouahri, 2019). The coastal regions cover 19 districts, comprising 32 per cent of the country's total area, and accommodate more than 35 million people (Haque, 2006; Alam et al., 2017). The impact of climate change on rising sea levels could accelerate saltwater intrusion into fertile soils and increase salinity from the north to the south and from the surface to downwards (Dasgupta, Hossain, Huq, & Wheeler, 2015; R. S. Das, Rahman, Sufian, Rahman, & Siddique, 2020). In the coastal regions, salinity has increased by an average of 26–33 per cent over the last 35 years (Mahmuduzzaman, Ahmed, Nurruzzaman, & Ahmed, 2014; Rahman et al., 2018).

Rice production is the principal source of the rural population's food, employment, and income in Bangladesh, providing nearly 48 per cent of rural employment (BBS, 2018). About 92 per cent of farming households are engaged in rice cultivation, which covers nearly 75 per cent of the total cropped area (BBS, 2018; BRRI). Stress-prone areas are typically major rice-producing areas where farmers depend on rice cultivation to support their livelihood. Raising the productivity of rice in this region is key to reducing poverty. Higher rice productivity not only directly increases the quantity of food available to poor households but also raises the income of poor and landless households where family members are employed as hired labour for rice production. However, climate risks pose an increasing threat to rice production by poor and vulnerable farmers in these areas. Flooding causes a loss in rice production by an average of 4 per cent of the total production annually (Paul & Rasid, 1993). Farmers lose around 9 per cent of their rice harvest because of flood-, drought- and salinity-related issues (Thomas et al., 2013). These losses negatively affect the food security of rural households, who depend mostly on agricultural income.

To reduce the rice production variability, the Bangladesh Rice Research Institute (BRRI) and Bangladesh Nuclear Research Institute (BINA) have developed and promoted several stress-tolerant rice varieties (STRVs) supported by the International Rice Research Institute (IRRI). Submergence- and salt-tolerant crops are the pragmatic approach for sustaining productivity and ensuring food security in a challenging environment (Jat et al., 2019). The adoption and effectiveness of each STRV differ for individual farmers, depending on regional, local, and farmer-level contexts. However, the diffusion process is often incomplete despite its potential benefits. Although these STRVs were developed about a decade ago, evidence of their adoption at the farmers' level is still limited.

This study aims to assess factors affecting the adoption of two kinds of STRVs, namely, submergence-tolerant rice varieties and salinity-tolerant rice varieties, in rural Bangladesh using extensive sample panel data. This research may contribute to the growing literature on the study of the adoption of STRVs. While a few previous studies have examined the effects of adopting submergence-tolerant rice varieties, research on the adoption of salinity-tolerant rice varieties is scarce. Additionally, previous research has relied solely on cross-sectional data. This study uses panel data, which is better able to capture yearly or seasonal variations, as well as adoption trends. Therefore, the findings can shed light on guidelines for effectively adopting STRVs by addressing the barriers to adopting new technology.

This paper is structured as follows. Section II provides a brief description of the materials and methods. Section III presents the results and discussions. Section IV provides the conclusions along with policy implications.

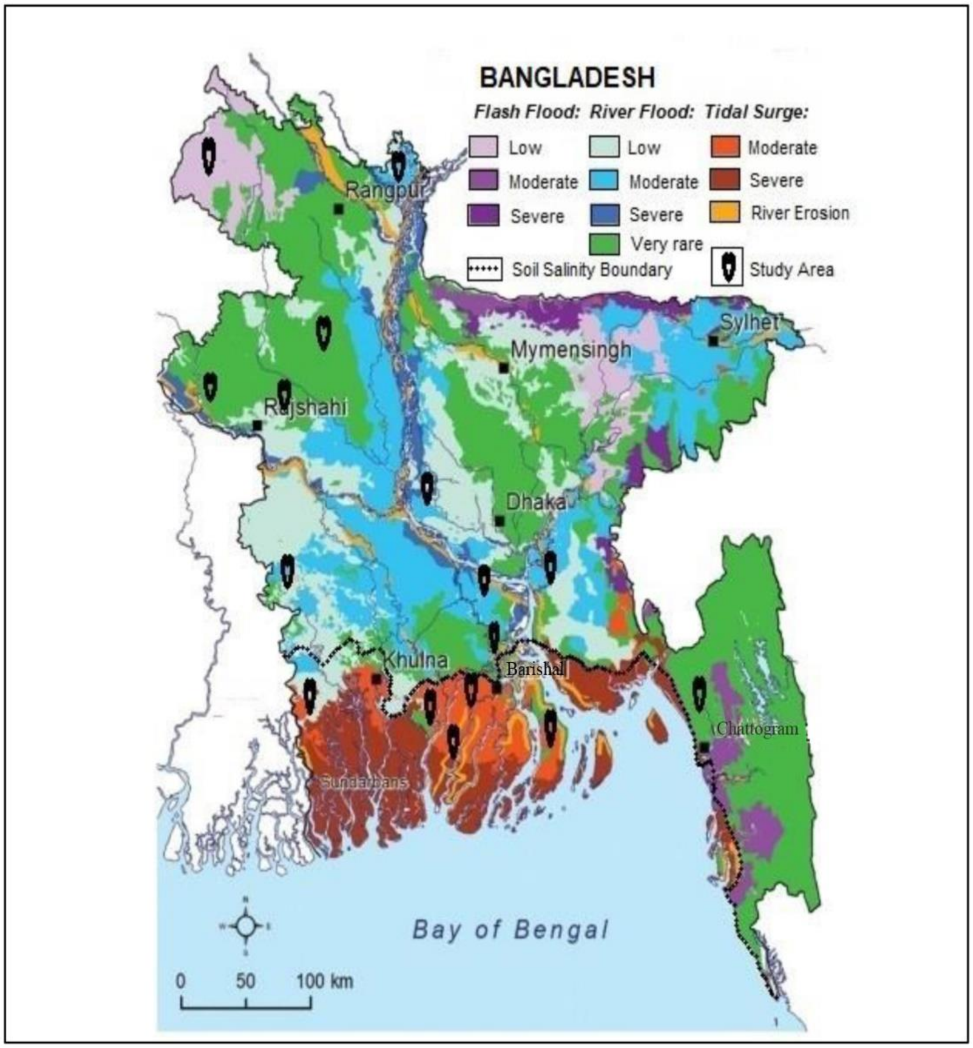
II. DATA AND METHODS

2.1 Farm Household Survey and Data

This study uses Rice Monitoring Survey in South Asia (RMS-SA) data from Bangladesh (Yamano, 2017). The data have been collected in two survey rounds by IRRI. The survey employed a multi-stage sampling method to select the divisions, districts, and villages (Yamano, Malabayabas, Panda, & Gupta, 2014). RMS is conducted in 150 villages of 16 districts across the six divisions of Bangladesh. The first-round survey was conducted in 2014, and 1,500 farm households were interviewed. In 2017, the second round of data collection was conducted, targeting the same households. Due to the unavailability of potential respondents in the household, 15 of the initial 1,500 households were unable to be re-surveyed in 2017. Therefore, this paper uses panel plot-wise data from 2014 and 2017, covering 1,485 households per round. The survey included high-quality data on socio-demographics, plot characteristics, plot-level agricultural practices, season-wise rice cultivation including STRV practices, asset and livestock ownership, abiotic or climatic stress information, access to information, social capital, and other subjects.

The study areas cover various climate-stress–prone districts of Bangladesh. The northeastern and southern, including coastal areas, are highly exposed to flooding, and salinity affects the coastal soils. Figure 1 depicts the location of the study sites, flood-prone and salinity-affected areas across 16 districts. The tidal flooding and direct inundation by saline water cause rising soil salinity. The soil salinity level in coastal regions ranges from 2 to more than 16 dS/m, reducing crop yield (SRDI, 2010).

Figure 1: Location of Study Sites, Flood-Prone and Salinity-Prone Areas in Bangladesh



2.2 Measurement of Key Variables

The STRVs considered in this study comprise submergence-tolerant rice varieties (SubTRVs) and salinity-tolerant rice varieties (SalTRVs). Submergence-tolerant cultivars include BRRI 51, BRRI 52, BINA 11, and BINA 12. These varieties are suitable for cultivation during the Aman (rainfed) season and can survive for at least 10–25 days under floodwater (Table 1). Cultivars of rice varieties that are adaptable to salinity comprise BR23, BRRI 40, BRRI 41, BRRI 47, BRRI 53, BRRI 54, BRRI 55, BRRI 61, BRRI 67, BRRI 73, BINA 8, and BINA 10, which are grown in the Boro (dry) or Aman (rainfed) season. The level of salt tolerance of these varieties ranges from 6 to 14 dS/m (Table I).

The adoption of SubTRVs and SalTRVs are the outcome variables of interest. These two variables are captured through a dummy variable at the household's plot level. The dummy variable takes the value of one if the new technology (any of SubTRVs or SalTRVs) is adopted on a plot during the year and zero otherwise. The explanatory variables in the adoption model are based on the study hypothesis, theory, and past empirical findings in the agricultural technology adoption literature. Plot features, household or farm characteristics, farm assets and resources, climatic stresses, and institutional and social capital are the five groupings of explanatory variables included in the model. Table II contains the list of explanatory variables.

The physical proximity of plots, soil characteristics, and farm size groups effectively influence the diffusion of new technology in developing countries (Feder, Just, & Zilberman, 1985; Conley & Udry, 2010; Gautam & Ahmed, 2019). Several plot-specific attribute variables are included in this study: the plot size, the number of plots held by a household, the land level of the plot, and plot tenure status. Plot size is defined as the total cultivated area of the plot. The land level of the plot was categorised into lowland, medium land, and upland. It is expected that farmers will be more likely to adopt STRVs if their plot is attributed to low and medium land types because those are more inclined to be submerged. Plot tenure status is an important determinant for the adoption of STRVs because before adopting any technology, farmers may consider whether the specific plot is their own or rented. It is assumed that tenant farmers are less likely to adopt STRVs as they do not feel secure compared to farmers who own their plots.

TABLE I

LISTS OF SUBMERGENCE AND SALINITY-TOLERANT RICE VARIETIES AND THEIR CHARACTERISTICS

Variety name	Planting season	Released year	Days to maturity	Average yield (t/ha)	Grain quality	Submergence tolerance (days)	Level of salt tolerance (dS/m)	Special features
BINA 11	Aman	2013	135[a], 120[b]	4.4[a], 5.2[b]	Medium long slender	25	-	Submergence tolerant, early maturing, low resistant to pests & diseases
BINA 12	Aman	2013	145[a], 130[b]	3.9[a], 4.4[b]	Medium short	26	-	Submergence tolerant
BRRI 51	Aman	2010	157[a], 142[b]	4.5	Medium bold	10-15	-	Submergence tolerant
BRRI 52	Aman	2010	155[a], 140[b]	5.0	Medium bold	10-15	-	Submergence tolerant
BINA 8	Boro	2010	135	5.0[c], 8.0[d]	Medium bold	-	12-14[m], 8-10[n]	Salt tolerant, early maturing, moderately resistant to pests & diseases
BINA 10	Boro/ Aman	2012	132	5.5[c], 7.5[d]	Medium long	-	12	Salt tolerant, early maturing, low resistant to pests & diseases
BR 23	Aman	1988	150	5.5	Long slender	-	6	Medium level salt tolerant
BRRI 40	Aman	2003	145	4.5	Medium bold	-	8-10	Salt tolerant
BRRI 41	Aman	2003	148	4.5	Long slender	-	8-10	Salt tolerant, resistant to pests & diseases
BRRI 47	Boro	2007	145	6.0	Medium bold	-	12-14[m], 6[n]	Salt tolerant
BRRI 53	Aman	2010	125	4.5	Long bold	-	8	Medium level salt tolerant
BRRI 54	Aman	2010	135	4.5	Long bold	-	8-10	Medium level salt tolerant
BRRI 55	Aus/Boro	2011	105/145	5.0/7.0	Long slender	-	9	Salt, cold, and drought resistant
BRRI 61	Boro	2013	150	6.3	Medium bold	-	12-14[m], 8[n]	Salt tolerant
BRRI 67	Boro	2014	145	6.0	Medium bold	-	12-14[m], 8[n]	Salt tolerant
BRRI 73	Aman	2015	125	4.8	Medium bold	-	8-13	Salt tolerant

Note: [a] under 20-25 days submerged condition, [b] non-submerged condition, [c] under salt stress, [d] non-saline areas, [m] seedling stage, [n] Life duration.

Data source: Adhunik Dhaner Chas, BRRI (2017), Digital Herbarium of Crop Plants (2017), BINA (2019).

TABLE II

DEFINITION OF VARIABLES USED IN THE ANALYSIS

Variables	Definition
Dependent variables	
SubTRVs	1 if farmers cultivated submergence-tolerant rice varieties; 0 otherwise
SalTRVs	1 if farmers cultivated salinity-tolerant rice varieties; 0 otherwise
Farmer characteristics	
Gender	1 if the farmer is male; 0 otherwise
Age	Age of household head in years
Education	Number of years of formal education by the farmer
Household size	Number of family members
Risk aversion	Total number of crops grown in a year in the same plot
Plot characteristics	
Crop loss due to flood	1 if the farmer experienced crop loss due to submergence; 0 otherwise
Crop loss due to salinity	1 if the farmer experienced crop loss due to salinity; 0 otherwise
Plot size (log)	Total cultivated area in decimal (log)
low land	1 if plot is low land; 0 otherwise
Medium land	1 if plot is medium land; 0 otherwise
Upland	1 if plot is upland; 0 otherwise
Separate plot	Total number of plots household owned
Rented plot	1 if the plot is rented in, 0 otherwise
Farm assets and resources	
Small farmer	1 if smallholder farmer (land size less than 2.50 acre); 0 otherwise
Medium farmer	1 if medium holder farmer (land size 2.50 to 7.49 acre); 0 otherwise
Large farmer	1 if large holder farmer (land size more than 7.50 acre); 0 otherwise
Distance to market	Distance from the nearest market (km)
Agricultural assets value (log)	Total value of household agricultural implements (BDT) per adult equivalent (log)
Social capital	
Sharing info with peer	1 if farmer received information from peers or farmers, 0 otherwise
Membership	1 if household is a member of any groups, cooperatives, etc., 0 otherwise
Contacting extension agents	1 if the farmer has access to advice from extension agents, 0 otherwise

Household-specific characteristics that can influence the adoption decision include the gender of the head of the household, their age, their education level, the household size, and farmers' risk aversion. Farmers with higher education are predicted to better appraise the significance of new technologies. Furthermore, bigger households are more likely to adopt new technology than smaller households (Abdulai, Monnin, & Gerber, 2008; De Souza Filho, Young, & Burton, 1999) because a bigger household could indicate a more secure labour source for a labour-intensive technology. Gender head, that is, whether the head of the household is male or female, and the age of the household head are also crucial factors to consider while adopting new technology (Bezu, Kassie, & Lafayette, 2014). The farmer's attitude to risk can also influence the adoption of technology. This variable is represented by the number of crops grown annually on the same plot. A risk-averse farmer follows crop diversification practices to minimise the risk of loss. In this adoption model, it is assumed that risk-averse farmers are more likely to be interested in cultivating STRVs because it may help to increase their utility and minimise production loss (Mariano, Villano, & Fleming, 2012).

Environmental disturbances or abiotic climate stresses, such as submergence, drought, and soil salinity, affect rice production. Among the plot-level disturbances, two major stresses, crop loss due to submergence and salinity in that plot and season, are included in the adoption model. It is hypothesised that if the farmers experienced crop loss due to submergence, flood, and salinity, they would be more likely to adopt the technology.

In terms of farm assets and resources, agricultural implements, the distance to the nearest input market, and farm size are included. The agricultural assets represent the value of per capita agricultural implements and machinery owned by the households. The per capita values are computed using adult equivalent units. It is hypothesised that households with a large value of agricultural implements are more likely to adopt the new technology because this ensures easily accessible resources. The distance between the farm and the input market can be used to determine market accessibility. A longer distance increases transaction costs and will thus constrain adoption. High transportation costs are associated with poor infrastructure and long distances from the markets (Binswanger, 1987; De Janvry, Key, & Sadoulet, 1997). Therefore, a greater distance from the market may significantly reduce the probability of technology adoption. Farm size groupings are divided into three categories based on the total amount of land owned by households: smallholder farmers (1 to 249 decimals), medium farmers (250 to 749 decimals), and large farmers (more than 750 decimals).

Social capital has been critical in promoting and diffusing technology adoption (Moser & Barrett, 2006; Wollni & Zeller, 2007; Wossen, Berger, & Di Falco, 2015). Farmers' acquisition of information and social learning have been shown to facilitate the successful adoption of new agricultural technologies (Feder & Slade, 1984; Wozniak, 1993; Bindlish & Evenson, 1997; Conley & Udry, 2010). Additionally, agricultural technical knowledge may be disseminated through informal routes, such as informal groups or farmer-to-farmer exchanges, and formal routes, such as extension agencies and membership in an organisation. The importance of extension in adopting new technologies has been widely recognised. Extension programmes can help farmers better understand and adopt new technologies (Hussain, Byerlee, & Heisey, 1994). In their study, Wossen et al. (2017) reported that extension access and cooperative membership positively affect technology adoption and welfare. Therefore, our model considers three social learning channels: extension services, farmers' membership in an organisation, and sharing information with peers or farmers.

2.3 Estimation Method

The adoption of SubTRVs and SalTRVs is analysed using a random-effects probit model with the Mundlak approach (Mundlak, 1978). In the panel model, this approach can overcome the incidental variables problem that fixed effects introduce in non-linear panel models and control the unobserved plot-specific effects. This approach relaxes the strict exogeneity assumption in the random effects estimator by allowing dependence between observed and unobserved variables. On the other hand, if the unobserved effect is invariant to time, the Mundlak approach allows for a correlation between the unobserved household omitted variable and variables of interest (Imbens & Wooldridge, 2007; Wooldridge, 2014). It allows for this correlation by including the mean of time-variant variables for the household and plot controls for bias that may arise from time-invariant unobserved heterogeneity (Cameron & Trivedi, 2005; Wooldridge, 2010).

A random utility framework can be used to model the decision of whether or not to adopt new technology (Asfaw, Shiferaw, Simtowe, & Lipper., 2012; Kassie, Jaleta, Shiferaw, Mmbando, & Mekuria, 2013; Teklewold, Kassie, & Shiferaw, 2013). Let a farm household i choose to adopt STRVs on one specific plot p if the utility of adoption (U_{ipA}) is higher than the utility of non-adoption (U_{ipNA}). The econometric representation used in this study is derived from Greene (2008) and Pham, Chuah, and Feeny (2021). The utility can be modelled for this study as expressed below:

$$y^*_{ipst} = X'_{ipst}\beta + v_{ipst} \tag{1}$$

where y^*_{ipt} is the outcome variable of interest (the decision to adopt SubTRVs and SalTRVs) referring to household i on plot p at time t adopting a practice of s. Here, y^*_{ipst} is unobservable and is defined as the latent variable. It is assumed that the unobserved y^*_{ipst} can be related to the observed variables X_{ipst} such as plot, farm, socio-economic and social factors. Here, v_{ipst} captures the unobserved factors. The binary outcome of a farmer's adoption decision y^*_{ipst} can be expressed as follows:

$$y_{ipt} = \begin{cases} 1 \ if \ y^*_{ipst} > 0 \\ 0 \ if \ y^*_{ipst} \le 0 \end{cases} \tag{2}$$

The probability of household i on plot p at time t with practice s is denoted as:

$$P\left(y_{ipst} = 1 \middle| X_{ipst}\right) = F(X'_{ipst}) \tag{3}$$

If the unobserved time-invariant variables (u_{ips}) and unobserved time-variant variables (ε_{ipst}) are included in the error term, then Eq. (1) can be rewritten as:

$$y^*_{ipst} = X'_{ipst}\beta + u_{ips} + \varepsilon_{ipst} \tag{4}$$

Now, to control for heterogeneity, we add the mean of time-variant variables, which is expressed as $\overline{m}_{ips}$ at household and plot level. From equation (iv), the unobserved time-invariant u_{ips} can be written as

$$u_{ips} = \gamma + \overline{m}'_{ips}\ \varphi + \epsilon_{ips} \tag{5}$$

Here, $\overline{m}'_{ipk\,.}\varphi$ is the time-variant in observed X_{ipst} at household and plot levels. Now from equations (iv) and (v), the probability of household i on plot p at time t can be rewritten as below:

$$P\left(y_{ipst} = 1 \middle| X_{ipst}\right) = F(\gamma + \overline{m}'_{ips}\varphi + X'_{ipst}\beta + \epsilon_{ips}) \tag{6}$$

By estimating equation (vi), φ is different from zero in the random-effects probit model with the Mundlak approach. Moreover, in the case of $\varphi = 0$, it becomes a standard random-effects model. The Wald test will be applied for robustness checking to see which approach best fits our model.

III. RESULTS AND DISCUSSION

3.1 Descriptive Statistics

Table III presents the descriptive statistics of the variables for SubTRVs and SalTRVs. Rice farmers, on average, have six years of education and six family members, and are 46 years old. Farmers experienced a crop loss of 26 per cent and 11 per cent of their total plots because of submergence and salinity stresses, respectively. Of the sample households of SubTRVs and SalTRVs, 25 per cent and 34 per cent of the total plots are rented, respectively. Households own an average of four plots. Although access to extension services is better in the study areas, very few farmers have membership in an organisation. About 11 per cent and 4 per cent of farmers adopted SubTRVs and SalTRVs, respectively, in 2017 (Figure 2).

TABLE III

DESCRIPTIVE STATISTICS OF EXPLANATORY VARIABLES, BY STRVs

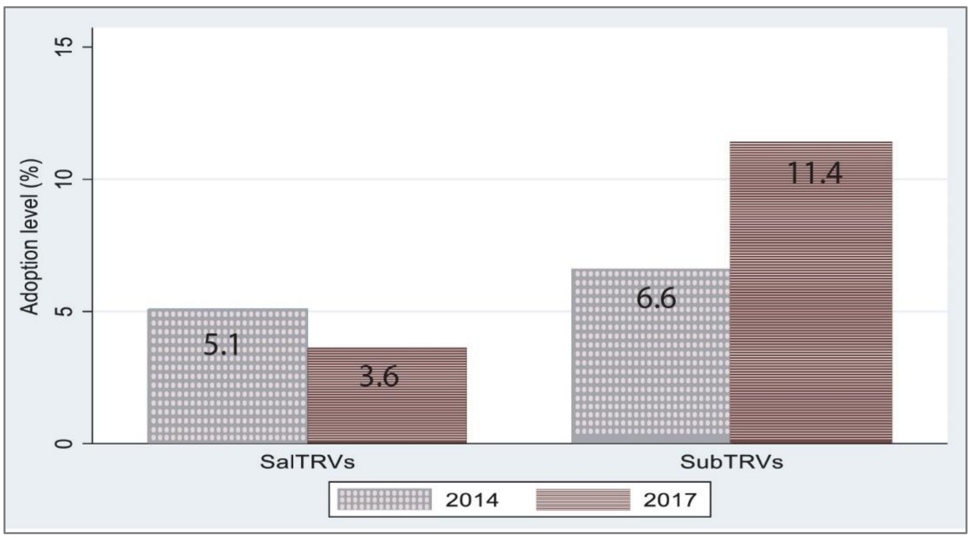
Variables	Submergence-tolerant rice varieties (SubTRVs) (N=6,011)		Salinity-tolerant rice varieties (SalTRVs) (N=3,491)	
	Mean	Std. Dev	Mean	Std. Dev
Farmer characteristics				
Gender	0.87	0.33	0.87	0.34
Age	46.45	13.11	46.46	13.18
Education	6.04	4.19	5.65	3.9
Household size	5.91	2.63	5.95	2.59
Risk aversion	1.41	0.64	1.33	0.54
Plot characteristics				
Crop loss due to flood	0.19	0.39	0.24	0.43
Crop loss due to salinity	0.05	0.21	0.07	0.26
Plot size (log)	3.84	0.89	3.68	0.90
low land	0.40	0.49	0.46	0.49
Medium land	0.51	0.50	0.48	0.50
Upland	0.08	0.27	0.06	0.24
Separate plot	3.75	2.17	3.99	1.98
Rented plot	0.25	0.43	0.34	0.47
Farm assets and resources				
Small farmer	0.76	0.47	0.84	0.47
Medium farmer	0.21	0.41	0.14	0.35
Large farmer	0.03	0.17	0.02	0.08

(Contd. Table III)

Variables	Submergence-tolerant rice varieties (SubTRVs) (N=6,011)		Salinity-tolerant rice varieties (SalTRVs) (N=3,491)	
	Mean	Std. Dev	Mean	Std. Dev
Distance to market	1.99	1.82	1.72	1.54
Agril assets value (log)	8.39	1.13	8.16	1.11
Social capital				
Sharing info with peers	0.24	0.42	0.20	0.39
Membership	0.17	0.38	0.16	0.37
Contacting extension agents	0.81	0.39	0.82	0.38

Note: Computed by the author based on the 2014 and 2017 Rice Monitoring Survey data, International Rice Research Institute (IRRI).

FIGURE 2: **Adoption Level of Submergence and Salinity Tolerant Rice Varieties by Household-Level**



Source: 2014 and 2017 Rice Monitoring Survey data, International Rice Research Institute (IRRI).

3.2 Determinants of Adoption of STRVs

The model with random effects with the Mundlak approach is estimated on plot-level observations. Estimated results from the random-effects probit model with the Mundlak approach for the SubTRVs and SalTRVs are presented in Table IV. The results show that the factors influencing STRV adoption may differ depending on the type of STRV because STRVs are zone-specific, require diverse agro-climatic conditions, and have specific traits. The estimated results also suggest that the Mundlak approach fits the data well and allows control of possible correlation of plot-invariant unobserved heterogeneity with observed covariates, which is crucial in our panel model analysis. Wald tests indicate that all coefficients of the mean of household and plot-varying covariates are jointly statistically different from zero for both models. Therefore, the Wald test confirms that the Mundlak approach is preferable to the standard random-effects model.

3.2.1 Farmers' Characteristics

The level of education of a farmer is a significant factor in adopting SubTRVs. Farmers who are more educated are expected to be more receptive and aware of new technologies. The estimated marginal effect of the variable is positive and statistically significant at the 1% level, indicating that for every year of additional schooling, the probability of adopting SubTRVs increases. On the other hand, age significantly and negatively influences the farmers' probability of adopting both STRVs, which means younger farmers are more likely to adopt SubTRVs.

TABLE IV

MARGINAL EFFECTS OF RANDOM-EFFECTS PROBIT MODEL WITH THE MUNDLAK APPROACH, BY STRVs

Variables	Submergence-tolerant Rice Varieties (SubTRV)		Salinity-tolerant Rice Varieties (SalTRV)	
	RE with Mundlak	RE	RE with Mundlak	RE
	(1)	(2)	(3)	(4)
Farmer characteristics				
Gender	0.028***	0.014**	0.016	0.009
	(0.010)	(0.007)	(0.013)	(0.005)
Age	-0.002*	0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Education	0.006***	0.001	0.001	-0.002***
	(0.002)	(0.001)	(0.003)	(0.001)
Household size	0.002	0.001	-0.006***	-0.005***
	(0.001)	(0.001)	(0.002)	(0.002)
Risk aversion	0.002**	0.015***	0.024**	0.001
	(0.001)	(0.005)	(0.013)	(0.004)
Plot characteristics				
Crop loss due to submergence	0.059***	0.008	-	-
	(0.014)	(0.007)		
Crop loss due to salinity	-	-	0.090**	0.012*
			(0.036)	(0.007)
Plot size (log)	-0.011**	-0.016***	0.004	-0.001
	(0.004)	(0.004)	(0.005)	(0.002)

(Contd. Table IV)

Variables	Submergence-tolerant Rice Varieties (SubTRV)		Salinity-tolerant Rice Varieties (SalTRV)	
	RE with Mundlak	RE	RE with Mundlak	RE
	(1)	(2)	(3)	(4)
low land	0.004	0.001	0.014	0.008
	(0.007)	(0.007)	(0.018)	(0.009)
Medium land	0.027***	0.012	0.006	0.013
	(0.009)	(0.009)	(0.017)	(0.009)
Separate plot	-0.006*	-0.004**	0.008	0.002***
	(0.004)	(0.002)	(0.005)	(0.001)
Rented plot	-0.035**	-0.022	-0.017*	0.001
	(0.016)	(0.016)	(0.010)	(0.004)
Farm assets and resources				
Small farmer	0.025***	0.020**	0.033***	0.014***
	(0.009)	(0.008)	(0.012)	(0.005)
Medium farmer	0.032	0.023	0.030	0.012
	(0.020)	(0.018)	(0.027)	(0.012)
Distance to market	-0.003	-0.004	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)
Agril assets value (log)	0.009***	0.008***	-0.008	-0.001
	(0.003)	(0.003)	(0.007)	(0.002)
Social capital				
Sharing info with peers	0.069***	0.062***	0.072***	0.084***
	(0.020)	(0.017)	(0.009)	(0.008)
Membership	0.034***	0.032***	0.023**	0.009*
	(0.009)	(0.009)	(0.011)	(0.005)
Contacting extension agents	0.006	0.011	0.015***	0.008**
	(0.012)	(0.007)	(0.004)	(0.004)
Year (2017)	0.016**	0.009	-0.007**	-0.005
	(0.007)	(0.006)	(0.003)	(0.003)
Barishal division	0.152***		0.128***	
	(0.028)		(0.015)	
Chattogram division	0.109***		0.029*	
	(0.029)		(0.017)	
Khulna division	0.096***		0.057***	
	(0.030)		(0.014)	
Rajshahi division	0.080***			
	(0.029)			
Rangpur division	0.111***			
	(0.028)			
Joint significance of mean of plot and household varying covariates	61.78		34.73	
Prob> χ^2	0.0000		0.0000	
Observations	6,011		3,491	
Number of plots	3,932		2,316	

Notes: Computed by the author based on the 2014 and 2017 Rice Monitoring Survey data, International Rice Research Institute (IRRI). REwithMundlak= Random-effects probit model with Mundlak approach, treat columns (1) and (3). RE= Random-effects probit model, treat columns (2) and (4). The mean of time-varying variables and divisional dummies are included in the random-effects probit model with the Mundlak approach model. 2014 is the base case of the year. Dhaka division is the base case of the location. Owned land is the base case for land tenure. Large farmer is the base case for farm size. Standard errors are in parentheses. Significance levels: 10%*, 5%**, 1%***.

The probability of adopting STRVs decreases if the household has a female household head. The significant result indicates that male-led households are 0.03 times more likely to adopt SubTRVs as compared to female-led ones. This may be because households with female heads are more likely to plant varieties with which they are familiar and are often reluctant to use new technology. The marginal effect of male-led households is positive but insignificant in adopting SalTRVs.

The estimated marginal effect of household size on the likelihood of adopting SalTRVs is negative and significant at the 1% level, suggesting that bigger households are less likely to adopt these rice varieties. These findings indicate that the bigger households may have other income sources, which reduces the household's interest in adopting new technology. The farmers' risk attitudes are represented by the crop diversification variable in the model. Crop diversification is thought to be used by risk-averse farmers to reduce the risk of crop failure. The estimated marginal effect indicates that their attitude towards risk influences farmers’ adoption of both SubTRVs and SalTRVs. Hence, this technology would be one of the effective adaptation strategies in climate stress-prone areas.

3.2.2 Plot Characteristics

The number of plots cultivated by a household and plot size is negatively and significantly correlated with the probability of adopting SubTRVs. The results reveal that even operating with a few number of cultivation plots, farmers are encouraged to adopt these rice varieties.

The estimated marginal effect of land level indicates that the medium land plot is positively associated with adopting SubTRVs. Farmers are, on average, more likely to plant these rice varieties on their medium land plots as compared to their upland plots. It is because medium land plots are more prone to be flooded. On the other hand, whether the plot is lowland or medium land does not affect the probability of adopting SalTRVs.

The marginal effect of land tenure (rented plot = yes) is statistically significant at the 5% level for SubTRVs and the 1% level for SalTRVs. The negative association with the adoption decision suggests that the likelihood of adopting SubTRVs and SalTRVs is smaller (0.02 and 0.04 times, respectively) for a rented plot than for an owned plot. These results are consistent with previous work related to technology adoption, which showed that a secure land tenure encourages the adoption decision (Teklewold et al., 2013).

3.2.3 Climatic Stresses

Crop loss on their plot as a result of climate stress has a significant effect on the farmers' adoption decision. Farmers who have experienced crop loss due to submergence are 0.06 times more likely to adopt SubTRVs. Similarly, farmers who have lost paddy because of salinity issues are 0.09 times more likely to adopt SalTRVs than those who did not experience such losses.

3.2.4 Farm Assets and Resources

The marginal effect of the smallholder farmer is positively and significantly correlated with the adoption of both SubTRVs and SalTRVs. This result implies that smallholder farmers are 0.03 times more likely to adopt both SubTRVs and SalTRVs as compared to large farmers. These findings indicate that smallholders stand to gain the most from the adoption of SubTRVs and SalTRVs. It is because these households are the most dependent on agriculture for their incomes and have fewer adaptation tools, both formal and informal, at their disposal to manage climate risks outside of agriculture.

The estimated marginal effects show that farmers' adoption of SubTRVs is linked to agricultural asset holding. The result indicates that farmers with fewer agricultural implements are less likely to adopt SubTRVs. Agricultural resource constraints are perhaps a barrier for many smallholders in adopting new technologies. In the case of SalTRVs, this parameter is negatively correlated with adoption but has an insignificant effect.

3.2.5 Social Capital

The presence of extension workers who educate farmers and inform them about new technologies was found to be a significant determinant of SalTRV adoption in this study. The marginal effect of the extension service is positive and significant at the 1% level. This finding indicates that the farmers who receive services from an extension agency are 0.02 times more likely to adopt SalTRVs than farmers who do not receive such services. It is noted that the access to extension services is exogenous to the individual farmer's choice. The effect of this variable is insignificant in the case of SubTRVs.

The result shows that social learning through farmer groups significantly impacts the adoption of STRVs. Farmers who have joined a group or organisation are more likely to be informed about the benefits of technology adoption, which increases their likelihood of adopting STRVs. The marginal effects of membership related to the adoption of SubTRVs and SalTRVs are positive and statistically significant at the 1% level (Table IV). This implies that adopters who had a membership in a farmers' group or other organisation increased their adoption of both these rice varieties by 0.02–0.03 times more than the farmers with no such membership.

The results also suggest that sharing information with peers positively and significantly correlates with the probability of adoption of SubTRVs and SalTRVs. This social learning through networking increases the likelihood of adoption of SubTRVs and SalTRVs by 0.07 times compared to households unaware of peers. These results confirm the previous research on technology adoption (Lapple & Kelley, 2015).

IV. CONCLUSIONS AND POLICY IMPLICATIONS

Climate-related disturbances not only have devastating effects on food security but also make it challenging to achieve the 2030 Sustainable Development Goals (SDGs) target of ending hunger and poverty. Understanding farmers' individual features and factors that could influence their behaviour is essential for disseminating any farm-level technology effectively. This study assesses the determinants of the adoption of STRVs in Bangladesh using panel data from IRRI for 2014 and 2017. In the adoption model, we included a variety of socio-economic, biophysical, and social factors that would help to understand the impediments to and present needs of farmers for the dissemination and adoption of STRVs. The correlations found are logical and consistent with the theory of technology adoption.

The results of the study show that the gender and education level of the household head, the farmer's risk aversion, crop damage due to exposure to flood, the number of plots, land type, whether the farmer is a smallholder, the farmer's agricultural implements value, membership in an organisation, and sharing information with peers all play an important role in influencing the farmers' probability of adopting SubTRVs. On the other hand, the adoption decisions of SalTRVs are influenced by household size, the farmer's risk aversion, crop damage due to salinity issues, whether the farmer is a smallholder, membership in an organisation, sharing information with peers, and receiving assistance from an extension agency. It was found that extension programmes are an important instrument for motivating farmers to adopt SalTRVs but have no significant role in the probability of adopting SubTRVs in the study areas. The role of agricultural extension is to provide information, technical advice, education, and training to help farmers make productive, sustainable use of their land. Farmers would be encouraged to adopt appropriate technologies if effective dissemination of information is there through extension services and other channels. Hence, an extension programme can play an essential role in sharing proper information, facilitating interaction among farmers, and motivating farmers to form their own groups and networks. However, extension services are often ineffective for smallholder farmers with respect to the introduction of modern technology in agriculture. Even though the stated goal of agricultural extension is to help underprivileged farmers, it often ends up supporting only better-off farmers. Moreover, the extension agencies and other government agricultural organisations have their own extension systems to serve their target groups. Non-government organisations (NGOs) and the private sector also provide extension services for their interests. Therefore, a policy with specific extension services and a technology transfer scheme for a target group of farmers is needed to encourage the adoption of STRVs. A partnership of IRRI, BRRI, farmers' organisations, and government extension agencies should be built to jointly implement farmers' capacity enhancement activities and information campaigns.

Rice farmers in Bangladesh are often smallholders cultivating tiny plots of land; according to our research, these farmers are more likely to use both types of STRVs. This finding indicates that STRVs could be an option for poor smallholders and climate-stress–prone communities and can help improve resilience. Therefore, an initiative aimed at promoting the adoption of STRVs among these farmers should be emphasised. Encouraging a larger number of smallholder farmers to participate in the demonstration and training is a possible solution for removing barriers. Extension agents should use the rice fields of smallholder farmers as demonstration sites for the new technology. As a result, the farmers might gain more knowledge and begin trusting the benefits of STRVs, and they could subsequently impart this learning to their neighbours and peers. Additionally, given the importance of social and institutional capital, it is imperative to strengthen local institutions and promote a community group–based approach to accelerate and maintain the adoption of STRVs. Implementing and adapting actions to effectively disseminate information and reducing the barriers to farm-level adoptions are necessary.

This study is based on panel data, which helps us conduct a more comprehensive analysis of farmer behaviour in the adoption of STRVs over time. Moreover, using a random-effects probit model with the Mundlak approach allowed us to control for unobserved time-invariant plot heterogeneities. However, there are a few limitations of this study. First, observations did not account for consumer taste, preferences, and market prices of the specific varieties, which may influence the technology adoption decision. Second, this study included two rounds of panel data with a small gap between these two periods. However, the new technology takes time to accrue. Hence, another panel survey could provide more visible results of adoption. The findings from this study can be corroborated and expanded upon by conducting follow-up studies in other settings.

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